# The Credit Line Channel

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**Abstract**

Aggregate bank lending to firms expands following a number of adverse macroeconomic shocks, such as the outbreak of COVID-19 or a monetary policy tightening. Using loan-level supervisory data, we show that these dynamics are driven by draws on credit lines by large firms. Banks that experience larger drawdowns restrict term lending more — crowding out credit of smaller firms. Using a structural model, we show that credit lines are necessary to reproduce the flow of credit toward less constrained firms after adverse shocks. While credit lines increase total credit growth, their redistributive effects exacerbate the fall in investment.

**Keywords:** Banks, Firms, Credit Lines, Monetary Policy, COVID-19

**JEL Codes:** E32, E43, E44, E52, E60, G21, G32

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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 the financial accelerator and the credit channel, among the most influential mechanisms in modern 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, an adverse shock that increases spreads or tightens credit constraints should create downward pressure on firm borrowing, worsening the drop in real activity.

Perhaps surprisingly, bank lending to firms *increases* following adverse shocks in a number of important cases. For a prime example, Figure 1.1 shows that over the weeks following the March 2020 U.S. COVID-19 outbreak — a period featuring a dramatic fall in consumer demand and massive layoffs — commercial and industrial (C&I) lending by U.S. banks grew rapidly. This phenomenon was specific to firm lending, with consumer and real estate loans remaining effectively unchanged over this period. This pattern is not restricted to acute crises, but is also observed following more typical macroeconomic disturbances, such as monetary policy shocks. To show this, Figure 1.2 displays impulse responses to an identified monetary policy shock based on the approach of Romer and Romer (2004). While consumer and real estate lending decline following a contractionary shock, we once again observe a significant rise in C&I lending. This pattern is robust to a wide array of specifications and identification schemes, presented in Appendix A.[1]

While these events by themselves do not prove or disprove any feature of the financial accelerator or the credit channel, whose predictions are relative to a world absent credit frictions, they provide a valuable setting to consider a number of important questions.[2] At the aggregate level, why does credit rise following these adverse shocks, and how do firms circumvent the highly intuitive contractionary forces predicted by theory? At the micro level, how is this overall increase in credit allocated across the firms in the economy, and what does it imply for investment and output? Finally, what effect does this credit surge have on the banking sector and its ability to intermediate funds?

In this paper, we seek to answer these questions using detailed loan-level data to document empirical relationships and a structural model to interpret them. To preview the main mechanism, our resolution of this puzzle centers on the role of credit line facilities.

[1] Importantly, our analysis focuses only on bank credit to nonfinancial firms and does not include other nonbank lending. In Appendix A.3, we use quarterly data from the Flow of Funds and show that the finding that firm borrowing increases in response to a monetary policy tightening still holds when taking into account alternative sources of firm financing. Similarly, total firm credit increased around the outbreak of COVID-19. Based on the Flow of Funds data, total loans and debt securities to nonfinancial businesses rose by around 4.7 percent comparing end-of-period levels in 2019:Q4 and 2020:Q1.

[2] In contrast, these findings *do* provide evidence against theories in which firms face binding constraints on bank credit, most of which unambiguously predict that bank credit should fall in these episodes.

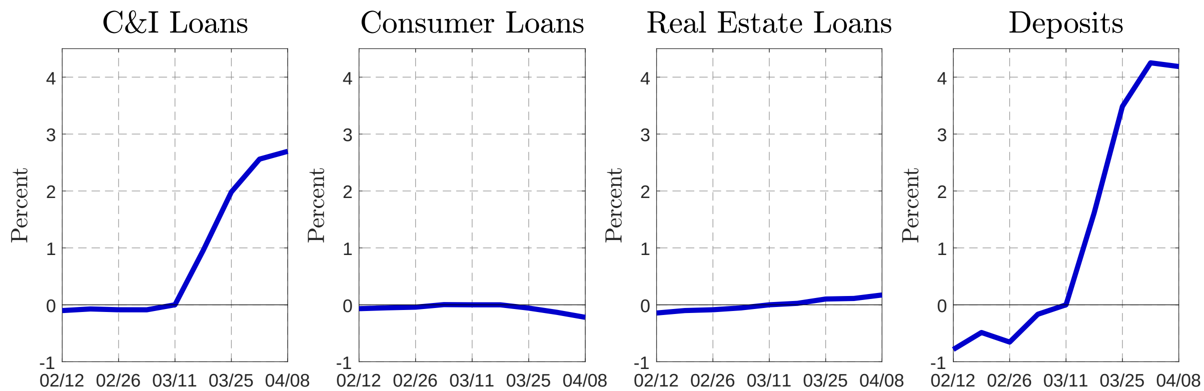


Figure 1.1: U.S. commercial banks' balance sheets around the start of COVID-19.

**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 and obtained from St. Louis Fed's FRED database. See Table B.1 in Appendix B.1 for details about the data.

Importantly, the pricing and terms of existing credit lines remain largely fixed following adverse shocks, even if credit spreads on new loans rise. As a result, firms with the ability to draw on credit lines are able to sidestep the deterioration in lending conditions in bad times, dampening the impact of negative shocks. At the same time, credit line drawdowns may not be wholly beneficial. We show that access to credit lines is overwhelmingly skewed toward the largest and seemingly least financially constrained firms in the economy. As these larger, less-constrained firms draw down their credit lines, they put pressure on the balance sheets of their lenders, who may therefore restrict lending to constrained firms even more than they would in an economy without credit lines. We refer to this mechanism, operating at both the aggregate and cross-sectional levels, as the *credit line channel* of transmission.

Our empirical study of the credit line channel centers on the FR Y-14Q data set (Y14), created by the Federal Reserve System for the purpose of conducting bank stress tests. This data set contains loans made to firms by large U.S. commercial banks over the period 2012 to 2020. Compared to standard U.S. data sets, which are often restricted to public firms and available at low frequency or at origination only, our data cover more than 200,000 private firms and are updated quarterly. Importantly, the Y14 data offer detailed information on loan characteristics unavailable in alternative data sets, most importantly distinguishing between term loans and credit lines, and between used and undrawn credit.[3] Our data have widespread coverage, on the order of half of all C&I lending

[3]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 partly for separations into committed and utilized 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 for commercial banks, the Consolidated Reports of Condition and Income

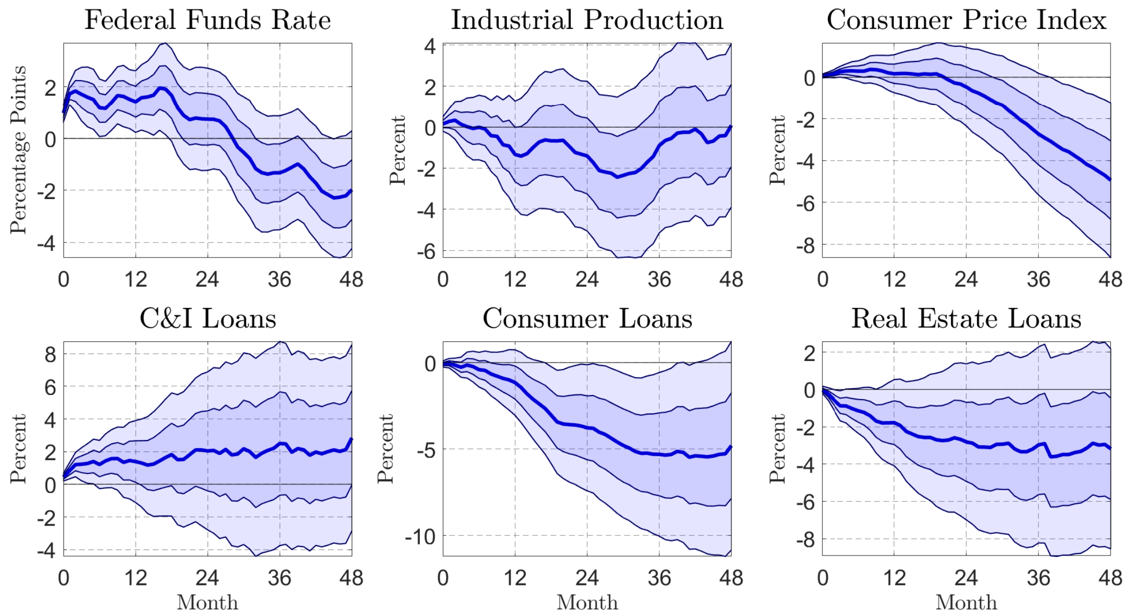


Figure 1.2: Impulse Responses to a Monetary Policy Shock.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the identification approach by Romer and Romer (2004). The shock series is taken from Coibion et al. (2017) and the remaining data are obtained from St. Louis Fed's FRED database. The credit series are based on the H.8 releases for U.S. commercial banks from the Board of Governors of the Federal Reserve (see Table B.1 in Appendix B.1 for details about the data). Sample: 1970:M1 - 2007:M12, the shocks in 1980:M4 - 1980:M6 and 1980:M9 - 1980:M11 are excluded following Coibion (2012). 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors. See Appendix A for details on the estimation, robustness, and further evidence.

by U.S. commercial banks over our sample. In addition, we refine and expand the data on firm financials using information from Compustat and Orbis - Bureau van Dijk (Orbis).[4] Equipped with this unique merged data set, we are able to provide a detailed empirical account of bank credit for U.S. firms, and investigate the micro-level forces that explain the aggregate responses shown in Figures 1.1 and 1.2.

We begin by documenting a set of facts about the composition and distribution of firm credit. At the aggregate level, credit lines account for more than half of all used bank credit in our data. But beyond this already large volume of used credit lies a massive reserve of committed but undrawn balances on credit lines. Strikingly, these undrawn balances are more than 40 percent larger than the total used balances on bank credit lines and term loans *combined*. Next, we show that in addition to these large aggregate levels, credit lines also play a dominant role in driving credit dynamics at the firm level,

("Call Reports"), or the Consolidated Financial Statements for Bank-Holding Companies (FR Y-9C) do not separate used credit into credit lines and term loans.

[4]Besides the information on credit arrangements, an additional advantage of the Y14 data is its wide coverage on balance sheets and income statements of private firms. Such information is typically difficult to obtain, and our analysis shows that the data coverage substantially exceeds that of other data sets that provide such information, as, for example, Dun & Bradstreet or Orbis, in particular for recent years.

explaining most of the variation in observed credit growth for all but the smallest firms in our sample. Last, we find that the distribution of both used and undrawn credit is highly skewed, with more than 40 percent of used credit, and approximately 70 percent of undrawn credit, accruing to the top 10 percent of the firm size distribution.

We next investigate what characteristics determine a firm's access to credit lines. We find that a number of attributes associated with reduced financial constraints, such as size, age, and profitability, all predict positively whether the firm has access to a credit line, as well as the undrawn capacity on the firm's credit lines. Our findings reinforce and expand those of Sufi (2009) and Campello et al. (2011), whose studies had previously relied on hand-collected firm data, to a much broader set of public and private firms.

After documenting these patterns, we directly investigate the role of credit lines in driving firm responses to shocks. We first examine idiosyncratic firm events, using local projections similar to Jordà (2005), to estimate the response of credit to a drop in cash flows. We estimate that firms increase credit by around 50 cents over the first year following a $1 drop in cash flows, and that this effect is entirely driven by an increase in credit lines. We find no evidence of a response of term loans, pointing to credit lines as the key margin of adjustment in response to firm cash flow shocks.

Turning to macroeconomic shocks, we revisit our impulse responses to an identified monetary policy shock, showing that the puzzling rise in bank-firm credit following a monetary contraction is entirely accounted for by an increase in credit lines, while term loans actually decrease. Decomposing this result by firm characteristics, we find that this increase in credit lines is in turn almost completely driven by large firms with extensive preexisting borrowing capacity.

To study the response to a more acute macroeconomic shock, we examine the role of credit lines during the COVID-19 outbreak. This episode represents a unique macroeconomic event to study changes in firm credit, as it entailed a steep fall in expected cash flow for many firms and was largely unanticipated. We show that the sharp rise in bank credit shown in Figure 1.1 is almost completely explained by an increased drawdown of existing credit facilities, rather than new credit issuance (Acharya and Steffen, 2020; Li, Strahan and Zhang, 2020). This increase in drawdowns is not evenly distributed across the size distribution but instead flows overwhelmingly to the largest 10 percent of firms (Chodorow-Reich et al., 2020).

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 a crowding out of lending for firms that rely on term loans. Using the fixed effects approach of Khwaja and Mian (2008) on the population of firms with term loans from multiple banks, we find that banks experiencing larger drawdowns on their credit lines contract their term lending by more. Surprisingly, the negative effect of these credit line draws is not offset at all by the large deposit inflows observed over this period as visible in Figure 1.1, leading us to conclude that our credit supply effect is more likely driven by regulatory limits, market-based constraints, or risk aversion by banks, rather than a direct scarcity of bank funds.

Taken together, our empirical results suggest that credit lines are central to the transmission of macroeconomic shocks to firm credit. To connect our results to the general equilibrium implications of credit lines on firm credit and investment, we turn to a structural model. To accommodate our results on firm heterogeneity, our setup features two types of firms: smaller "constrained" firms that face a binding minimum on their dividend payouts, and larger "unconstrained" firms that do not. Each type of firm prefers debt finance due to a tax shield, but faces covenant violation risk that increases with firm leverage. Lenders face convex funding costs, so that spreads on new term loans increase as firms obtain more term loans or draw their credit lines. To study the model's response to an adverse macroeconomic shock, we consider a negative shock to productivity.

We first show that a model in which both type of firms use term lending fails to match our empirical findings, counterfactually predicting that the relative share of credit held by constrained firms increases following an adverse shock. This occurs because unconstrained firms have more elastic demand for credit due to their flexible dividend margin, leading to a relative decline in credit as spreads rise. Beginning from this baseline, we introduce credit lines, which allow unconstrained firms to borrow at a predetermined, fixed spread. With unconstrained firms now insulated from rising spreads, they borrow heavily, crowding out lending to constrained firms, and reproducing the distributional pattern observed in the data. These results imply that credit lines are structurally important for credit transmission, producing dynamics that are sharply different from models with term lending only.

The overall impact of credit lines on the response of firm investment to adverse macroeconomic shocks depends on the composition of two forces. First, credit lines create an *aggregate effect*, increasing total credit growth. Since investment is increasing with credit for both types of firms, this force dampens the drop in total investment following the shock. At the same time, credit lines create a *distributional effect*, by reallocating credit from constrained to unconstrained firms. Since the investment of constrained firms is more sensitive to credit than that of unconstrained firms, which largely use additional credit to smooth dividends, this force amplifies the drop in total investment following the shock. Under our benchmark calibration, the distributional effect dominates, leading to a larger drop in investment than under a model with term lending only. Overall, our results indicate that credit lines are not merely a convenient instrument for borrowing, but structurally central to the aggregate and cross-sectional dynamics of credit and investment following an adverse shock.

**Related Literature.** Our paper relates to a large literature on the transmission of macroeconomic shocks through credit markets.[5] For example, the credit channel of monetary policy posits that the "direct effects of monetary policy on interest rates are amplified by endogenous changes in the external finance premium" (Bernanke and Gertler, 1995). Importantly, an increase of bank-firm credit after a monetary tightening should not be taken as support against such a channel.[6] Instead, we view our results as evidence that amplification mechanisms, such as the credit channel of monetary policy, are mitigated for a subset of firms — those with credit lines — and, as a result, are even stronger for other firms. In this regard, we contribute to a growing literature that emphasizes the heterogeneous effects of macroeconomic shocks, with several recent contributions focusing on firms' responses to changes in monetary policy.[7] In the credit channel literature, our work is perhaps closest to Gertler and Gilchrist (1993*a*), who similarly study the rise in credit following contractionary monetary shocks, and also argue that this increase is biased toward larger firms. Our paper complements their work by demonstrating the centrality of credit lines in driving this phenomenon, and studying their impact on the aggregate and cross-sectional consequences for firm credit and investment.

Further, we relate to a literature on the use of credit lines from a firm's perspective. Several papers find that credit lines are an important source of funding for firms in times of distress (Jiménez, Lopez and Saurina, 2009; Berg, Saunders and Steffen, 2016), such as the 2007-09 financial crisis (Campello, Graham and Harvey, 2010; Berrospide and Meisenzahl, 2015), or they are used to exploit investment opportunities (Lins, Servaes and Tufano, 2010). Brown, Gustafson and Ivanov (2020) use weather events as instruments for cash flow shocks and find that firms use their credit lines to smooth out such shocks. Interestingly, our estimates are very close to theirs, despite the different empirical specifications. We contribute to this literature by showing that credit lines are "special," in the sense that firms use them more after a fall in their cash flow, but they do not employ other types of bank credit in the same way.

Closer to the bank's perspective, the pricing structure of credit lines is found to depend on the level and cyclicality of usage rates (Berg et al., 2017); they are also costlier for firms with higher liquidity risk or higher aggregate risk exposure (Acharya et al., 2014; Acharya, Almeida and Campello, 2013), and banks with liquidity exposure on the funding side may face greater pressure on the asset side from credit line drawdowns (Ippolito

[5]See e.g., Bernanke, Gertler and Gilchrist (1999), Gertler and Gilchrist (1994), among many others, and Lian and Ma (2020) for a recent example.

[6]The distinctive response of C&I loans following a monetary policy shock has been recognized previously (see, e.g., Gertler and Gilchrist, 1993*b*, Kashyap and Stein, 1995, and den Haan, Sumner and Yamashiro, 2007).

[7]Examples of recent papers are Ottonello and Winberry (2018), Crouzet and Mehrotra (2020), Jeenas (2019), Cloyne et al. (2019), Bahaj et al. (2020), Darmouni, Giesecke and Rodnyansky (2020), and Anderson and Cesa-Bianchi (2020), among others, which build on the work by Gertler and Gilchrist (1994).

et al., 2016). Moreover, banks restrict credit more often due to covenant violations if their own health deteriorates (Acharya et al., 2019; Chodorow-Reich and Falato, 2020), and access to credit lines is found to be more contingent on overall credit conditions for private firms than for public ones (Demiroglu, James and Kizilaslan, 2012). Our contribution to this literature is to document that off-balance-sheet credit lines may result in a substantial reallocation of credit and restriction of term lending when a large number of firms draw on their existing credit lines. Ivashina and Scharfstein (2010) and Cornett et al. (2011) provide similar evidence for the 2007-09 financial crisis, with the difference that the Khwaja and Mian (2008) approach allows us to clearly isolate the credit supply effect within this context.[8,9]

Finally, we connect to the literature relating bank credit lines and deposit flows. This literature argues that banks have a comparative advantage in providing firms with credit lines because they typically experience an inflow of deposits at the same time when firms draw on their credit lines (see e.g., Kashyap, Rajan and Stein, 2002; Gatev and Strahan, 2006), with this comovement depending on whether bank deposits are insured and can be seen as a safe haven in crisis times (e.g., Pennacchi, 2006; Acharya and Mora, 2015). Indeed, as shown in Figure 1.1, bank deposits strongly increased after the outbreak of COVID-19, precisely during the large credit line draws we document. While in principle these offsetting flows could counteract the credit supply effect we estimate, we find not only that our result is unchanged controlling for deposits, but that deposit flows have an effect close to zero on the supply of term loans over this period. Thus, while our results reinforce the comovement suggested by this literature, they imply that the available liquidity during this episode does not neutralize banks' economic exposure to credit line draws.

**Road Map.** The rest of the paper proceeds as follows. Section 2 describes the data, while Section 3 establishes several key stylized facts. In Section 4, we provide evidence on the use of credit lines and borrowing capacity in the cross-section of firms and show how firms adjust their credit usage in response to cash flow changes. In Section 5, we revisit the evidence in Figures 1.1 and 1.2, and study the behavior of firm credit to a monetary policy shock and around the outbreak of COVID-19. Section 6 presents a macroeconomic model with credit lines. Section 7 concludes.

[8]In this regard, we contribute to a literature that estimates the effects of bank-specific shocks on firm outcomes, including Khwaja and Mian (2008), Schnabl (2012), Jiménez et al. (2012), Chodorow-Reich (2014), and Huber (2018), among others. Luck and Zimmermann (2020) and Bidder, Shapiro and Krainer (2019) have used the Y14 data in this context.

[9]See also the debate between Chari, Christiano and Kehoe (2008) and Cohen-Cole et al. (2008) with respect to the 2007-09 financial crisis.

# 2 Data

We assemble the data for our empirical analysis from a variety of sources. All loan information on bank-firm relationships and contract terms comes from the FR Y-14Q H.1 collection for commercial loans. The Y14 data consists of information on loan facilities with over $1 million in committed amount, held in the portfolios of bank holding companies (BHCs) subject to the Dodd-Frank Act Stress Tests.[10] 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.[11]

We restrict the sample to 2012:Q3 - 2020:Q2. The starting point gives a more even distribution of BHCs in each quarter and also affords a short phase-in period for the structure of the collection and variables 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.[12] Our analysis therefore focuses on bank credit to nonfinancial firms and does not cover nonbank credit, bank credit by non-Y14 banks, and firms that are outside of our data set.

The great strength of the data is its rich cross-sectional information and its unparalleled view into loan contracting arrangements for a broad spectrum of firms, especially smaller and non-publicly traded ones. In particular, we observe both committed and utilized exposure of the credit facilities, allowing us to more precisely estimate a firm's used and unused borrowing capacity. Our primary way of identifying a distinct firm is through the taxpayer identification number (TIN).[13] There are 205,477 distinct TINs observed in the Y14 over the sample period, among which we are able to identify 2,344 as public firms.[14]

The firm financial statement variables are combined from three sources: Compustat, the Y14, and Orbis. We opt to use financial statement data from the quarterly Compustat files whenever possible because the 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. For each firm at each date, we select the median value for the firm

[10] A loan facility is a lending program between a bank and a borrower organized under a specific credit agreement. Facilities 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. See also footnote 19.

[11] 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 in this study, the size threshold was set at $50 billion. In 2019, the threshold was increased to $100 billion.

[12] Appendix B.3 describes these sample restrictions and additional ones in more detail.

[13] The TIN does not always correspond to the economic definition of a firm. However, for instances where the two differ, the TIN may still be a good representation if borrowing decisions are made according to the tax liability within or across firms (see also Chodorow-Reich, 2014, for a discussion).

[14] Public firms are identified as the ones that can be matched to Compustat data.

financial variable over all observed BHC loan facilities and all BHCs. Since the firm financial data should be the same across loans and across banks, this approach of taking the median observed value helps eliminate reporting errors as well as increase the number of dates for which we have observations on each firm's financial characteristics. In addition, if a variable is also observed for a private firm in Orbis, then we average the variables from the two sources as a way of further reducing measurement error.[15] However, such instances are rare and the main advantage of the Orbis data is that it 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.[16]

None of our data sources for firm characteristics have information on lending covenants. To bridge this gap, we use heuristic covenant formulae taken from Dealscan and apply them to the firm financial statement data (see Appendix B.2 and Section 3 for details).[17] All nominal variables are deflated using the consumer price index for all items and is taken from St. Louis Fed's FRED database (Index 2015 = 100). Tables with variable descriptions, data sources, and a list of cleaning and data filtering steps are left to Appendix B.

# 3 Descriptive Evidence

In this section, we establish several key stylized facts demonstrating the importance of credit lines for aggregate and cross-sectional credit patterns. We show that credit lines not only make up the majority of used bank credit in our sample, but also hold vast reserves of unused capacity that are even larger than the volume of total used credit. In addition to these large balances on average, we show that for the vast majority of firms, variation in credit line use accounts for the majority of variation in total loans over time. Finally, we show that credit line access and unused capacity are overwhelmingly concentrated

[15] Specifically, if the Y14 and Orbis data do not differ by more than 5 percent for a particular firm-date observation, then we average the variables from the two sources but exclude the observation otherwise. However, there are only few cases when we integrate information on firm financials from Orbis or disregard observations because of differences with the Y14 data, and all results in the paper are robust to omitting the firm financials data from Orbis. For example, for the most populated variables, we are only able to integrate around 250 observations per quarter. That is because the coverage of firm financials for private firms decreased in Orbis around the start of our sample. As mentioned in the text, the main advantage of integrating the Orbis data comes from obtaining a measure of firm age.

[16] To obtain an accurate measure of firm age, we also use the Field-Ritter data set of company founding dates for public firms (Field and Karpoff, 2002; Loughran and Ritter, 2004). In particular, the Field-Ritter date is used whenever the value in the Orbis data is missing or the Field-Ritter founding date is older than the one according to Orbis. The data are available at: https://site.warrington.ufl.edu/ritter/files/2019/05/FoundingDates.pdf

[17] See Berrospide and Meisenzahl (2015) for a similar approach to including covenants, and also Demiroglu and James (2011) for descriptions of other constraints on borrowing, such as "material adverse change" clauses.

Table 3.1: Summary Statistics.

| | Total | Credit Lines | Term Loans |
|---|---|---|---|
| Loan Facility Observations | $4,510,295$ | $58\%^a$ | $42\%^a$ |
| Used Credit | 943 | $53\%^b$ | $47\%^b$ |
| Fixed Rate | $23\%^b$ | $5\%^b$ | $14\%^b$ |
| Variable Rate | $77\%^b$ | $48\%^b$ | $33\%^b$ |
| Committed Credit | $2,241$ | $78\%^c$ | $22\%^c$ |
| Fixed Rate | $18\%^c$ | $6\%^c$ | $9\%^c$ |
| Variable Rate | $82\%^c$ | $62\%^c$ | $23\%^c$ |

**Notes:** The table shows summary statistics of the Y-14Q data for the sample 2012:Q3 - 2019:Q4. Committed and used credit are quarterly averages in billion U.S. Dollars, in 2015 consumer prices. See Section 2 and Appendix B for details about the data. Notation: $^a$percent of total number of loan facilities with observed loan information, $^b$percent of total used credit with observed loan information, $^c$percent of total committed credit with observed loan information.

among the largest, most creditworthy firms, and exhibit skewness even beyond what is observed for total credit. We focus on the sample 2012:Q3 - 2019:Q4, before the start of the outbreak of COVID-19 in the United States, and therefore representative of an economy in "normal times."

Summary statistics on loan characteristics are presented in Table 3.1. For the 2012:Q3 - 2019:Q4 period, the data cover around 4.5 million loan facility observations.[18] In terms of counts, 58 percent of the observed facilities over the sample period are labeled as credit lines, with the remaining 42 percent as term loans. The vast majority of both loan contract types are variable-rate loans. These data show that credit lines are a central form of bank credit for our sample of firms, representing 53 percent of total used credit. In addition to these used balances, we document that credit lines have enormous quantities of credit that has been committed by lenders but not yet drawn. These undrawn balances are in fact nearly 40 percent larger than total used credit on both credit lines and term loans, representing a vast source of potential financing. Taking together used and unused credit, we find that credit lines account for the majority of credit committed by banks (78 percent).

Figure 3.1 shows that these patterns are stable over time, and in particular that unused borrowing capacity substantially exceeds actual used credit throughout the sample.[19] We

[18]Over the sample 2012:Q3 - 2019:Q4, the total loan volume of used credit that the data cover is around 50 percent of the total loan volume of the C&I loan data in the H.8 releases of the Federal Reserve. However, our sample also covers loans to firms that are not classified as C&I loans, such as loans to firms secured by real estate. Throughout the sample, around 82 percent of the loans in our sample are considered C&I loans according to the definition in the H.8 releases.

[19]Note that Figure 3.1 includes "unused credit" and does not differentiate between unused credit lines and term loans. As noted in footnote 10, loan facilities can include both credit lines and term loans, but are classified in the Y14 on the basis of which loan type accounts for the largest share of the committed amount.

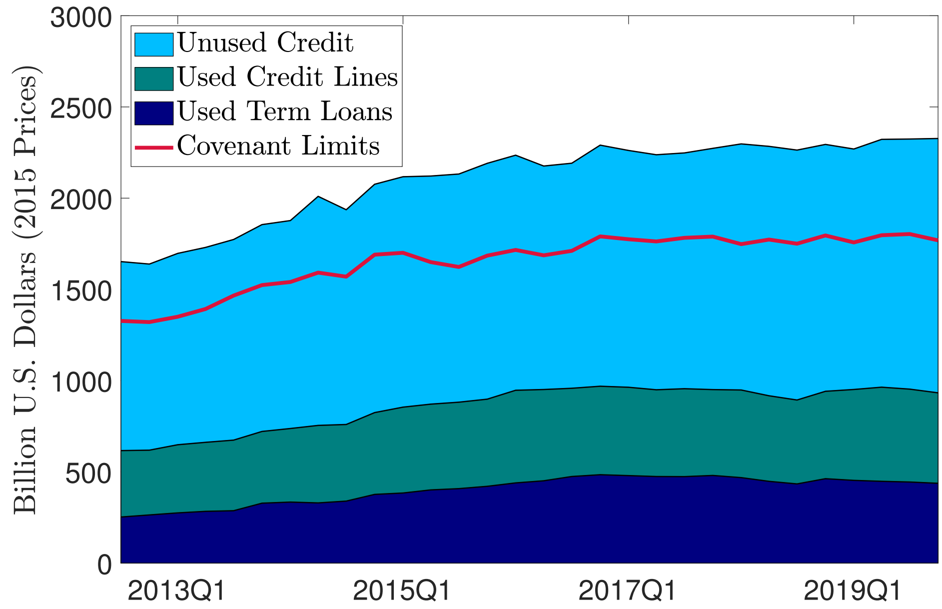


Figure 3.1: Aggregate term loans and credit lines.

**Notes:** The figure shows the total amount of term loans and credit lines across all banks in billion U.S. dollars and 2015 consumer prices. Unused credit is given by the difference between committed and used credit of credit lines and term loans. Covenants may reduce firms' unused credit as indicated by the red line, which is computed by applying generic covenant rules at the firm-level (see Appendix B.2 for details). Sample: 2012:Q3 - 2019:Q4. See Section 2 and Appendix B for details about the data.

note, however, that not all of this capacity may be freely drawn in practice, since banks frequently include loan covenants in their lending facilities that restrict further drawdowns if a firm's condition deteriorates in some observable way. To address this, we apply typical ratios on the most common covenants observed in Dealscan: interest-coverage and debt-to-earnings covenants. Firm-by-firm, we compute the additional amount that could be drawn from credit lines without violating these assumed covenant limits. Scaled up to the aggregate level, this procedure generates the red line in Figure 3.1, representing covenant-adjusted undrawn capacity. The figure shows that, while covenant restrictions are nontrivial, roughly two-thirds of unused credit could be drawn without violating typical covenants, resulting in an aggregate borrowing capacity that is roughly the same size as total used credit (see Appendix B.2 for details about the calculations).

Turning to cross-sectional patterns, Figure 3.2 shows that the distribution of credit, both used and unused, is highly skewed across the firm size distribution. The largest 10 percent of firms account for around 50 percent of total used term loans and approximately

Average utilization rates for term loans are 94 percent in our sample, compared with 41 percent for credit lines. Around 96 percent of term loans are effectively fully utilized within 5 quarters of origination, while only 42 percent of credit lines are completely used at this point in time. While some portion of the unused term loan borrowing capacity may actually be associated with a term loan, the majority is likely accounted for by unused credit lines. We therefore assume throughout our analysis that unused term loans represent unused credit lines, or "unused credit" for short.

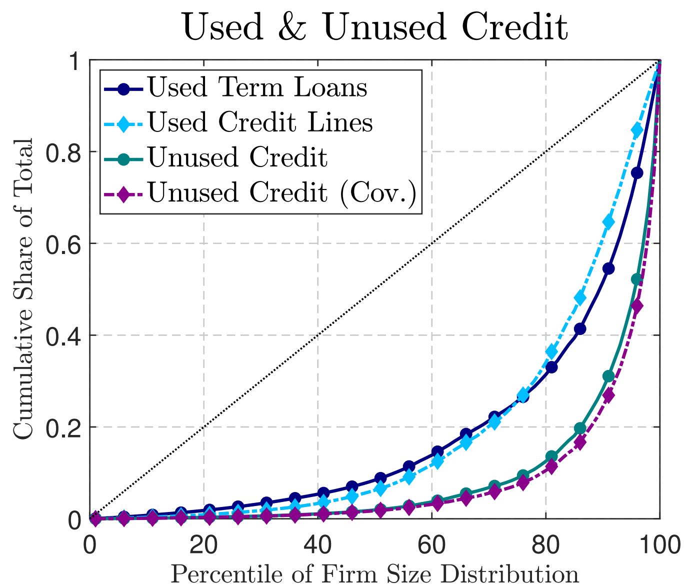


Figure 3.2: Cumulative Shares across Firm Size Distribution.

**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 given by the difference between all committed and used credit, and the covenant-adjusted version is computed by applying generic covenant rules at the firm level (see Appendix B.2 for details). The firm size distribution is obtained for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4. See Section 2 and Appendix B for details about the data.

40 percent of total used credit lines. To some degree, this skew reflects the fact that firm size itself is a skewed distribution.[20] Notably, unused credit is even more skewed than used credit, with the top 10 percent of firms accounting for more than 70 percent of the total unused credit available. This fact about our data is consistent with the notion that larger firms tend to be substantially less financially constrained than smaller firms.

Moving beyond the level of credit, we next investigate the role of credit lines in driving changes in firm credit over time. To do this, we define the variance of quarterly changes in term loans and credit lines relative to the variance of total credit, for firm $i$ by $Var_i^{Term} = Var_i(\Delta L_{i,t}^{Term})/Var_i(\Delta L_{i,t}^{Total})$ and $Var_i^{Line} = Var_i(\Delta L_{i,t}^{Line})/Var_i(\Delta L_{i,t}^{Total})$, respectively, where $\Delta L_{i,t}^{k}$ represents the quarterly change in used credit of type $k$ for firm $i$ at time $t$. Figure 3.3 shows these two variance shares for term loans and credit lines across the firm size distribution. For most firms, variation in credit line usage is the main driver of variation in total loans that are observed in the data. The ratio of total variance accounted for by credit lines is fairly uniform with changes in credit lines accounting for a consistent 60 percent of the total variation in loans from the 20th percentile to the 90th

[20]The data cover a large number of small and medium-sized enterprises (SMEs). For example, for 2016:Q4, the lower threshold for the top ten percent of the size distribution is \$550 million in total assets, \$21 million for the top 50 percent, and the maximum size for the bottom 10 percent is \$3.6 million.

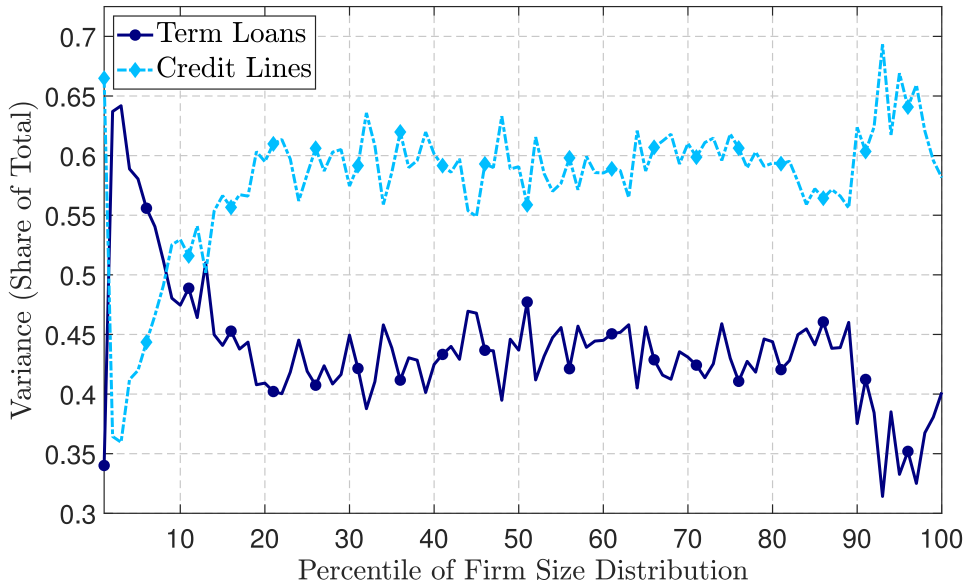


Figure 3.3: Variance Decomposition of Used Credit across Firm Size Distribution.

**Notes:** The figure shows the average variance of one-quarter changes in used term loans or credit lines, as a share relative to the variance of total used credit, across the firm size distribution. Because of nonzero covariance between changes in the two types of credit, the shares do not sum to unity. Firms with less than three years of data and observations within the top 5 percent tail of the pooled sample are excluded. A firm's size is measured by its average total assets. Sample: 2012:Q3 - 2019:Q4. See Section 2 and Appendix B for details about the data.

percentile of the size distribution.[21] Fluctuations in credit lines dominate fluctuations in term loans for all but the smallest firms in our sample. Importantly, this firm-level pattern would be partially obscured in the aggregated data, which would find $Var^{Term} = 0.44$ and $Var^{Line} = 0.34$. These results are consistent with credit lines as a key instrument for managing idiosyncratic firm shocks, leading to changes in credit that partially net out in the aggregate.

Firm size turns out to be a reliable proxy for the way credit characteristics and access to credit varies across firms in the sample. In Figure 3.4, we show that, as we move across the size distribution, the incidence of firms having credit lines increases monotonically from 60 percent for the smallest firms to nearly 100 percent for large firms (panel a, Figure 3.4).[22] Reliance on credit lines as a share of total used credit also trends upward, before

[21]For these calculations, we abstract away from a covariance term that would be included in a complete variance decomposition. However, throughout the firm size distribution, the covariance term is relatively small, since the sum of the two shares that are shown in Figure 3.3 is close to one.

[22]The fact that smaller firms have fewer credit line may depend on the fact that we observe only a subset of total firm borrowing. Smaller firms may obtain credit lines from smaller banks that are outside of our data. However, for the smallest within our data, we observe nearly all of their total debt (see Figure C.1 in Appendix C), and since these firms typically borrow from a single lender, it is unlikely that the documented pattern depends on the absence of data from small banks, unless the small firms outside of our data are substantially different than the small firms that we observe.

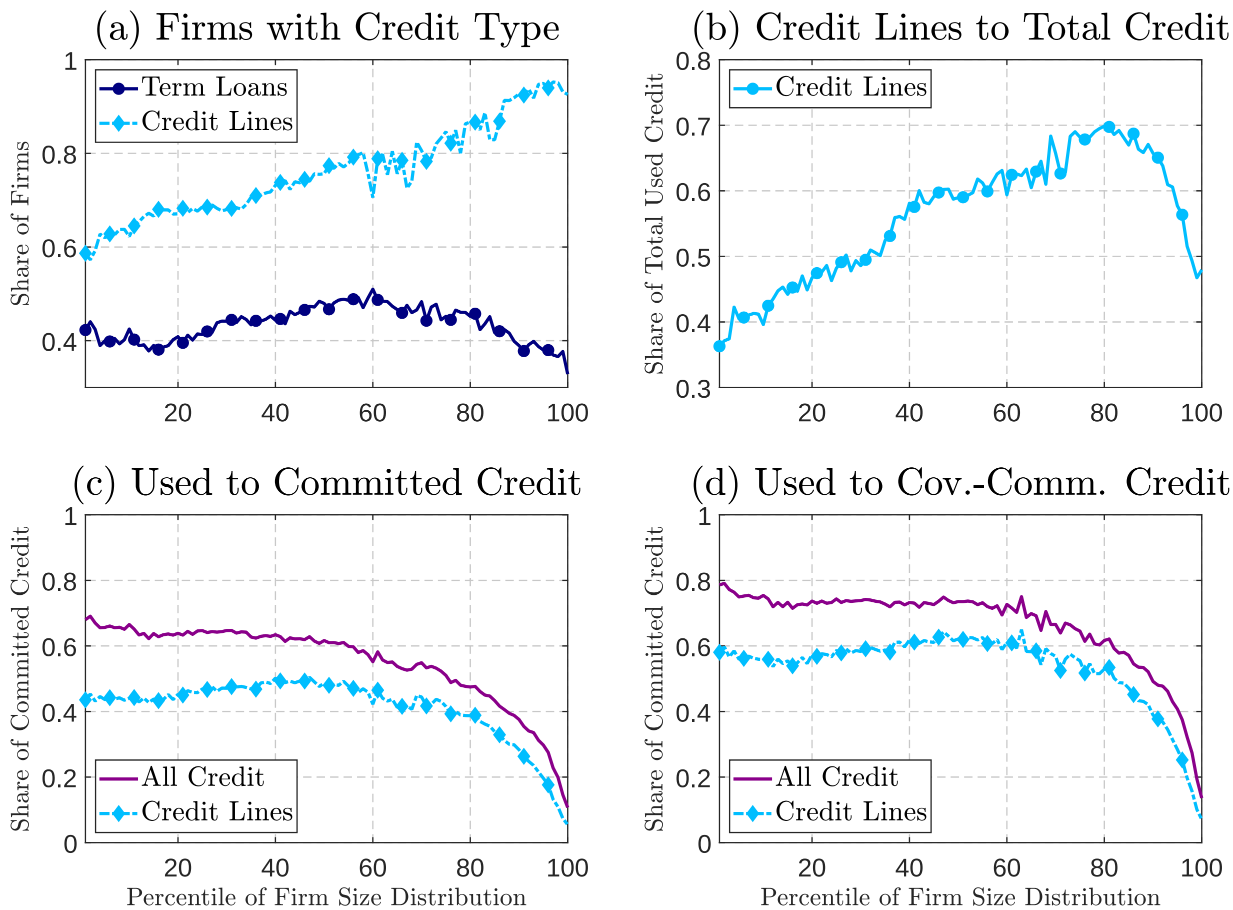


Figure 3.4: Credit Characteristics across Firm Size Distribution.

**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 used term loans relative to all used 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.2. The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4. See Section 2 and Appendix B for details about the data.

reversing somewhat for the largest firms in the sample (panel b, Figure 3.4).[23] As firms become larger, the ratio of used-to-committed credit falls (panels c and d, Figure 3.4).

Figure 3.5 shows that larger firms also generally face lower interest rates (panel a), are considered more creditworthy according to the banks' internal loan ratings (panel b), and are less likely to post collateral of some kind (panel c).[24] When firms do post

[23] This reversal in the upper tail is likely at least in part an artifact of how the data are constructed. Credit facilities are classified as term loans if the majority of committed credit takes the form of a term loan (see also footnote 19). However, firms at the top of the size distribution report large amounts of unused credit in their term loan facilities, indicating that term loan facilities for these firms must frequently also include large credit lines. Netting out these credit line balances would likely reverse much of the observed rise in the share of term loan credit at the top of the size distribution.

[24] The Y14 contains internal loan ratings for the obligors responsible for loan repayment. The Federal Reserve also collects a mapping of each bank's internal loan rating scale to a common Standard & Poor's

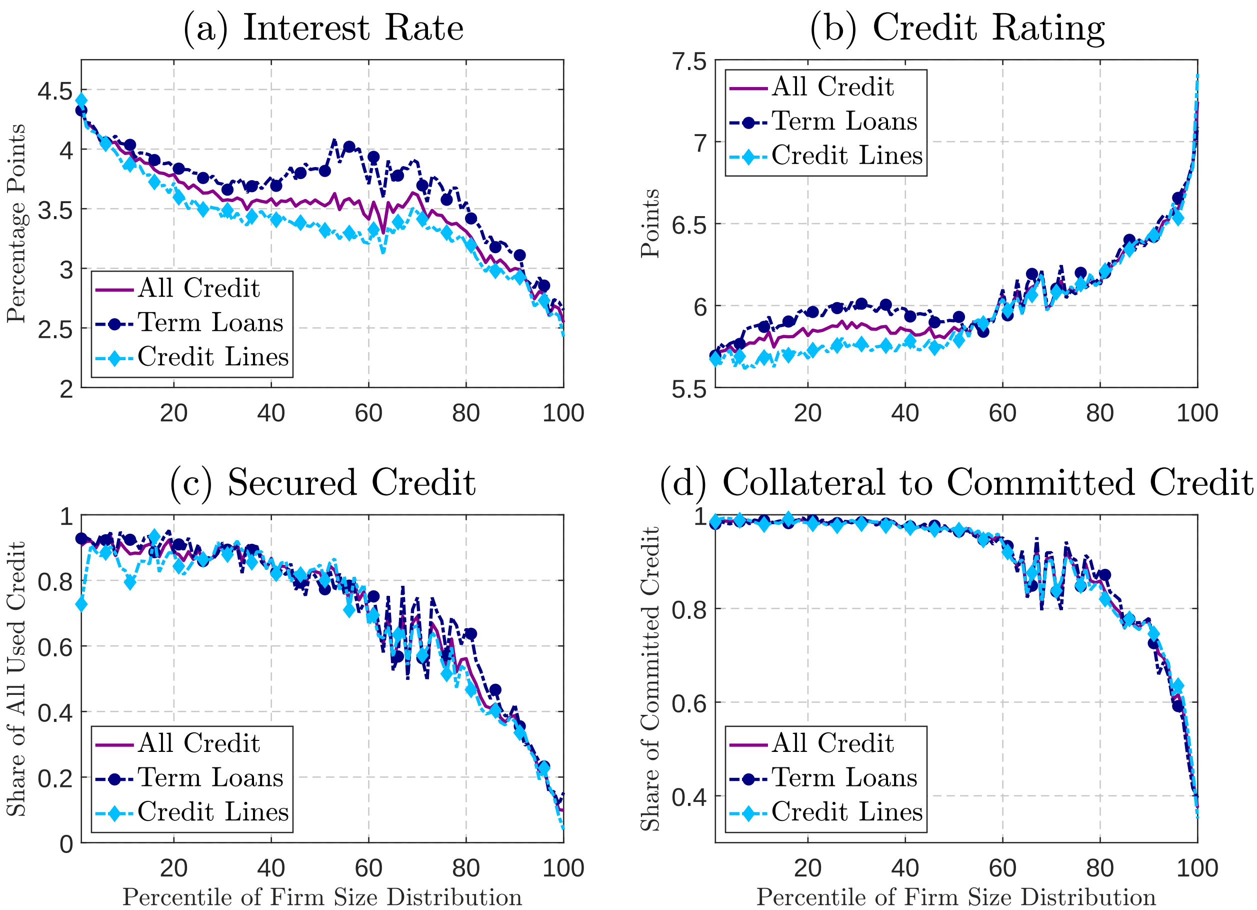


Figure 3.5: Credit Characteristics across Firm Size Distribution.

**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 (see footnote 24). Panel (c) displays the share of all credit that is secured by collateral. 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. See Section 2 and Appendix B for details about the data.

collateral, the value of the collateral relative to the loan commitment falls monotonically as firm size increases (panel d).[25] Figures C.1 and C.2 in Appendix C provide additional characteristics across the firm size distribution, showing that smaller firms are more likely to obtain 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., 2020).

Taken together, the 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 explain most

rating scale. In panel (b) of Figure 3.5, we assign a number to each distinct common rating, with the "best" rating given a 10 (AAA) and the lowest rating given a 1 (D).

[25]For these calculations, the value of collateral is set to the loan commitment amount if it exceeds this amount, that is, in cases when the loan is "over-collateralized."

firm-level variation in total loans in our data. Cross-sectionally, credit lines are an increasingly important source of bank funding for the largest firms which hold much of the unused borrowing capacity and may therefore play an outsize role in driving overall movements in credit.

# 4 Determinants and Use of Firm Credit

The choice of loan type and credit usage are endogenous to both borrower and lender. In this section, we present results from simple empirical models to provide some evidence on what determines these outcomes. We show that variables suggested by the theoretical literature, such as profitability, leverage, and various other proxies for the borrower's ability to repay, are all significant predictors of firm usage of credit lines and borrowing capacity in the cross-section. We also show how credit usage adjusts to changes in firm cash flows. We find that most of the adjustment is accomplished through credit lines, in particular by firms that have preestablished borrowing capacity.

## 4.1 Which firms have credit lines and borrowing capacity?

We explore specifications related to those in Sufi (2009) and Campello et al. (2011) to understand which type of firms have credit lines and borrowing capacity. To this end, we aggregate all credit indicators at the firm level and estimate regressions as

$$Y_{i,t} = \alpha_t + \tau_k + \boldsymbol{\beta X_{i,t-4}} + u_{i,t} \quad , \tag{4.1}$$

where the dependent variable $Y_{i,t}$ takes several forms. In column (i) of Table 4.1, we assess determinants of credit line adoption along the extensive margin. Here, the dependent variable is the log-odds ratio of a 0-1 variable, denoting whether firm $i$ has a credit line within our sample (that is, a positive committed balance). In column (ii), the dependent variable is the firm's level of unused borrowing capacity on credit lines (1-used credit/committed credit).[26] In column (iii), we construct a credit line intensity variable (unused credit/(unused credit + cash)) that measures the extent to which a firm relies on its observed credit line capacity relative to cash as a source of liquidity. For these three dependent variables, we adjust firms' unused and committed balances for covenants as described in Appendix B.2. All specifications include time ($\alpha_t$) and industry ($\tau_k$) 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 the firm's noncash assets. EBITDA and tangible assets

[26]Specifically, if we observe any unused borrowing on term loans, then such borrowing capacity is added to the committed balances of a firm's credit lines.

Table 4.1: Credit Line Regressions.

| | (i) Firm has Credit Line (Committed>0) | (ii) Unused Capacity (Unused/Committed) | (iii) Credit Intensity (Unused/(Unused+Cash)) |
|---|---|---|---|
| EBITDA | 1.52*** | 0.27*** | 0.25*** |
| | (0.10) | (0.01) | (0.01) |
| Tangible assets | -0.40*** | 0.18*** | -0.28*** |
| | (0.05) | (0.01) | (0.01) |
| Size | 0.09*** | 0.02*** | -0.03*** |
| | (0.01) | (0.00) | (0.00) |
| Leverage | -0.89*** | -0.58*** | -0.21*** |
| | (0.07) | (0.01) | (0.01) |
| Investment grade | -0.12*** | 0.12*** | 0.02*** |
| | (0.03) | (0.00) | (0.00) |
| Public firm | 0.65*** | 0.14*** | 0.02*** |
| | (0.07) | (0.01) | (0.01) |
| Firm age | 0.11*** | 0.02*** | 0.03*** |
| | (0.02) | (0.00) | (0.00) |
| R-squared | 0.10 | 0.27 | 0.12 |
| Observations | 181,780 | 145,547 | 142,368 |
| Number of Firms | 36,883 | 29,820 | 29,450 |

**Notes:** Estimation results for regressions (4.1). Dependent variables are {0,1}-indicator measuring whether a firm has a credit line in column (i), the share of unused borrowing capacity, defined as 1 minus the ratio of used balances to committed balance in column (ii), and a credit line borrowing intensity measure defined as the ratio of unused balances to unused balances plus cash in column (iii). The specifications include adjustments to borrowing capacity to reflect generic covenant restrictions as described in Appendix B.2. EBITDA and tangible assets are scaled by noncash assets (total assets minus cash and marketable securities). Size is defined as the natural log of noncash assets. Leverage is the ratio of total liabilities to total assets. Firm age is the natural log of number of periods between the observation date and firm incorporation date, annualized. All regressors are lagged by four quarters. The incidence of a firm having a credit line is estimated as a logit regression, reporting a Pseudo $R^2$. All other specifications are estimated using OLS. Sample: 2012:Q3 - 2019:Q4. All estimations include industry and time fixed effects. Standard errors in parentheses are clustered by firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

are scaled by the firm's noncash assets, while leverage is defined as total liabilities over total assets.[27] "Investment grade" and "Public" are dummy variables denoting whether a firm has an internal rating of BBB or better, and is publicly traded, respectively.

The results in column (i) of Table 4.1 show that credit lines are more commonly observed among large, old, and profitable firms with low leverage. These credit line adoption 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

[27] To eliminate outliers and data entry errors, observations within the 1 percent tails of the distributions for EBITDA, tangible assets (both relative to noncash assets), and leverage are excluded.

problems (e.g., Holmström and Tirole, 1998). The profitability variable and leverage are directly related to a firm's ability to repay debt. The other controls (size, public, and age) all have the expected signs and proxy the borrower's ability to repay. Only "Tangible assets" and "Investment grade" have unexpected signs in column (i), though the relations reverse when moving from the extensive to the intensive margin in column (ii).

The determinants of unused borrowing capacity in column (ii) of Table 4.1 are quite similar to the results for the extensive margin in column (i). Again, large, profitable, and old firms with low leverage appear to be rewarded with greater unused borrowing capacity. Hence, these results suggest that credit line access and the unused capacity on it are actually suitable indicators for firms' credit worthiness themselves, as they correlate with a number of variables that proxy how constrained firms are in their credit access (see, e.g., Cloyne et al., 2019).

These findings also carry over to the credit line intensity regressions (column (iii) of Table 4.1), showing that firms with these same characteristics tend to rely more heavily on unused credit lines for their liquidity needs, with the exception of firm size.[28] In Appendix D.1, we compare estimations with and without covenant adjustments (Table D.1) and split the sample into private and public firms for the specification without covenant adjustments (Table D.2). Broadly, specifications without covenant adjustments give similar results. In the private-public firm split, firm profitability is particularly important for explaining whether private firms have credit lines and how much unused capacity they possess, potentially because they are informationally more opaque.

## 4.2 Credit Responses to Cash Flow Changes

We next establish that credit lines are the primary bank credit instrument used by firms to smooth through shocks to their cash flows. In particular, we estimate credit responses by local projections,

$$\frac{L_{i,t+h-3} - L_{i,t-4}}{0.5\,(L_{i,t+h-3} + L_{i,t-4})} = \alpha_i^h + \tau_{t,k}^h + \kappa_m^h + \beta^h \frac{\Delta^4 CF_{i,t}}{Assets_{i,t-4}} + \boldsymbol{\gamma^h X_{i,t-4}} + u_{i,t-3}^h \tag{4.2}$$

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 between $t-4$ and $t-3+h$ as a dependent variable for two reasons.[29] First, the symmetric growth rate is able to accommodate

[28] Unobserved credit and firms may affect the estimations in Table 4.1. However, such missing observations are unlikely to reverse the main results, since we typically observe a smaller fraction of the total credit of large firms (see Figure C.1 in Appendix C), and incorporating such additional data could therefore strengthen the findings (see also footnote 22).

[29] The symmetric growth rate is the second-order approximation of the log-difference for growth rates around zero and has been used in a variety of contexts such as establishment-level employment growth

changes in credit from a starting level of zero, in contrast to a specification that uses the percentage change in firm credit. Second, the dependent variable is bounded between $-2$ and 2 for all impulse response horizons and therefore avoids the possibility of extreme outliers and the need to winsorize, which may also be the case when using the percentage change in credit. The coefficient of interest is $\beta^h$, associated with a firm's change in cash flow $\Delta^4 CF_{i,t}$ scaled by total assets. Given the different frequencies of variables in the data, the timing of the dependent variable and the regressors may differ. In particular, the change in cash flow is observed at an annual frequency, whereas the credit variables are available at a quarterly frequency, and we make use of the higher frequency and estimate regressions (4.2) at a quarterly frequency. $\Delta^4 CF_{i,t}$ denotes the change in cash flow over the quarters $(t-7)-(t-4)$ to $(t-3)-(t)$ . That is why the dependent variable considers changes in credit from $t-4$ to some future period.

All specifications include a firm-horizon fixed effect ($\alpha_i^h$), an industry-time-horizon fixed effect ($\tau_{t,k}^h$), and a location-horizon fixed effect based on the zip code of a firm's headquarters ($\kappa_m^h$) to account for possible changes in a firm's location over time. 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.[30] 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 that firms experience, we exclude absolute annual changes of $\Delta^4 CF_{i,t}/Assets_{i,t-4}$ that are larger than 5 percentage points.[31] As explained below, we check and confirm the robustness of our findings to this assumption.

The inclusion of the various control variables are intended to absorb non-cash flow drivers of firm credit, so that $\beta^h$ captures the remaining variation due to cash flow changes. Even so, interpreting $\beta^h$ as a causal estimate would face identification challenges.[32] Instead, our results focus on the differences in $\beta^h$ across credit categories, and can therefore be thought of as decomposing the roles of credit lines and term loans in driving the observed correlations of cash flow changes and credit growth at various horizons. To this

rates (see, e.g., Decker et al., 2014) but also credit growth rates (see, e.g., Gomez et al., 2020).

[30]Specifically, these regressors are $\Delta^4 CF_{i,t-4}/Assets_{i,t-8}$, $\Delta^4 CF_{i,t-8}/Assets_{i,t-12}$, $2 \cdot (L_{i,t-4} - L_{i,t-8}) \,/\, (L_{i,t-4} + L_{i,t-8})$, and $2 \cdot (L_{i,t-8} - L_{i,t-12}) \,/\, (L_{i,t-8} + L_{i,t-12})$.

[31]For the change in net income relative to assets that is used in the estimations, this assumption approximately corresponds to excluding observations below the 15th and above the 85th percentiles of the sample distribution. In addition to this restriction, the sample is also constrained to a balanced panel, and loan histories with time gaps are excluded.

[32]First, some of the cash flow changes may be anticipated in advance, and firms may have responded by altering their credit usage at the time when the news arrived. Second, regressions (4.2) may be subject to reverse causality or omitted variable bias. For example, firms that expect a new investment opportunity may take on new credit, which in turn leads to higher cash flows.

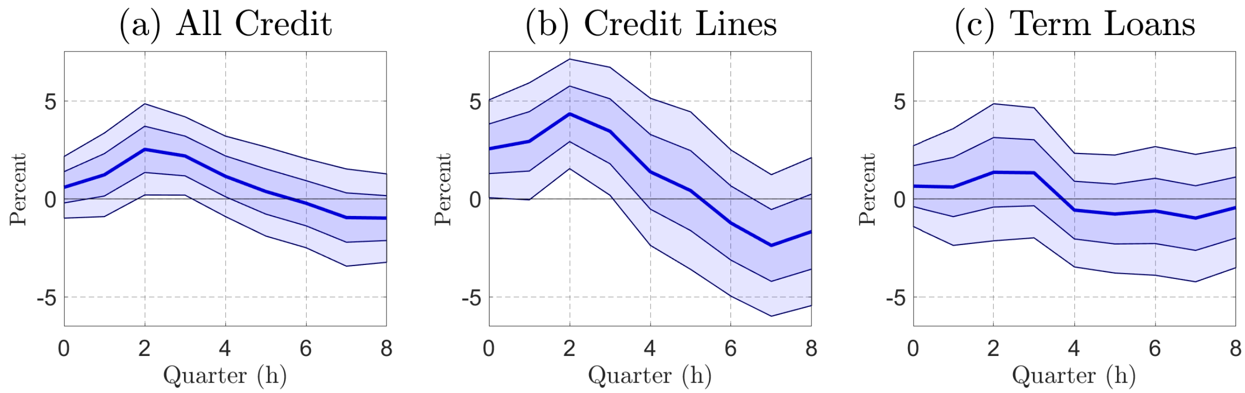


Figure 4.1: Credit Responses to a Cash-Flow Change.

**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 (4.2). Observations with absolute annual changes in net income relative to assets larger than 5 percent are excluded. The estimations are based on a balanced panel of credit lines and term loans and 1208 observations for each impulse response horizon. 95 and 68 percent confidence bands are shown using standard errors that are clustered by firm. Sample: 2012:Q3 - 2019:Q4.

end, we restrict the sample to firms for which we observe both credit lines and term loans.

Figure 4.1 shows the negative of the estimated coefficients $\beta^h$ to facilitate the interpretation, based on regressions with net income as a measure of firms' cash flow. After a fall in net income, firms increase their total use of credit immediately (panel a, Figure 4.1). The rise in credit to a negative cash flow change reaches a peak after two quarters, and actually becomes negative after around six quarters, indicating that firms' creditworthiness deteriorates in the medium run. Panels (b) and (c) in Figure 4.1 show that the rise in total credit is completely accounted for by the adjustment in credit lines. By contrast, there is no statistically significant adjustment in term loan usage.

The effects are also sizable. A one percent fall in net income relative to total assets is followed by an average 1.6 percent increase in total firm credit over the first year. Adjusted for firms' typical leverage in our data, this response implies that firms increase their total credit by around 50 cents for a $1 drop in net income over the first year.

In Appendix D.2, we provide further refinements of the responses. First, interacting the firm's cash flow change variable with lagged borrowing capacity shows that the adjustment in credit line usage is strongest for firms that have relatively more capacity prior to the cash flow change (see Figure D.1). Second, there is relatively little adjustment in committed credit lines to changes in cash flow. Instead, the response of credit is most clearly detected in a change in utilization rates of existing credit lines (Figure D.2). Third, we allow for larger absolute changes in net income relative to assets of up to 10 percent and find that the results remain much the same (Figure D.3). Last, Table D.3 lists the reported purposes for credit lines, with "Working Capital" and "General Corporate Purposes" accounting for the most frequent uses of credit lines.

# 5 Behavior of Firm Credit around Macroeconomic Events

The evidence so far shows that credit lines are used frequently by firms and potentially allow them to meet short-run liquidity needs following shocks to their cash flows. In this section, we study whether these findings at the firm-level also explain the response of credit to macroeconomic shocks in the aggregate and cross-section. In particular, we revisit the evidence from the introduction: the behavior of bank-firm credit to a monetary policy tightening and around the outbreak of COVID-19. We show that credit lines are the main driver of the increase in overall credit to these two types of adverse macroeconomic shocks. Central to this analysis is our ability to distinguish credit lines and term loans in the Y14 data, which would be impossible using typical U.S. bank-level datasets.

## 5.1 Credit Responses to Monetary Policy Surprises

To understand whether the responses in Figure 1.2 can be explained by an increase in credit lines after a monetary policy tightening, we take two approaches. First, to decompose the contributions to macroeconomic credit aggregates, we construct aggregate time series for term loans and credit lines based on the micro-data and estimate separate responses for each. Second, to study the cross-sectional reallocation induced by these shocks, we replicate the responses using firm-level data, which also allows us to decompose the aggregate response by prior firm characteristics.

Denote the total loan volume of some credit type at time $t$ across all firms and banks by $L_t = \sum_{i=0}^{N} L_{i,t}$. Based on these quarterly "aggregate" time series, we estimate impulse responses using the specification

$$\frac{L_{t+h} - L_{t-1}}{L_{t-1}} = \alpha^h + \beta^h \epsilon_t^{MP} + \boldsymbol{\gamma^h X_{t-1}} + u_t^h \quad , \tag{5.1}$$

where $h = 0, 1, ..., 8$ and $\epsilon_t^{MP}$ denotes the monetary policy shock at time t. Since the short-term policy rate was expected to remain at its lower bound for a large part of the sample for which the Y14 data is available, we use surprise movements in the two-year government bond yield as a measure of the shock. In particular, we employ the high-frequency identification approach as in Gürkaynak, Sack and Swanson (2005) or Gertler and Karadi (2015): the surprises are given by changes in the two-year government bond yield over a 30-minute-window around policy announcements (10 minutes before, 20 minutes after an announcement). The identifying assumption is that news about monetary policy dominates over such tight windows. To match the frequency of the Y14 data, we convert the surprises from a meeting-by-meeting frequency to a quarterly frequency by summing all meeting surprises within a quarter. We obtained the relevant data for the sample 2012:Q3 - 2019:Q2 and the quarterly shock series $\epsilon_t^{MP}$ is shown in Figure E.1 in Appendix E.1.[33] The vector $X_{t-1}$ collects several controls: two lagged values of the one-quarter growth rate of the dependent variable and two lags of the monetary policy shock.[34]

The coefficient of interest in (5.1) is $\beta^h$, which captures the response of credit at horizon $h$ to a monetary policy shock. Figure 5.1 shows the estimated coefficients, depending on whether the credit type are credit lines, term loans, or the sum of the two. Reassuringly, the response of all credit (panel a) takes a similar shape as that of Figure 1.2 for a more recent sample, showing an expansion of aggregate bank-firm credit following a surprise monetary tightening.[35] The two other panels decompose the drivers of this response into changes in credit lines and term loans, showing that the aggregate increase is entirely accounted for by an increase in credit lines, while term loans actually decrease. These responses suggest that, while firm credit demand increases following an adverse shock, to smooth spending or meet short-run liquidity needs, firms strongly prefer to borrow at the pre-negotiated terms set on their existing credit lines, rather than returning to the market for new credit at potentially higher spreads.[36]

In Appendix E.1, we provide additional robustness checks. First, we show that the results are similar when using the monetary policy surprise series by Nakamura and Steins-

[33]The high-frequency identification comes at the cost that the monetary surprises are relatively small: the standard deviation of the quarterly series is around 6 basis points. This prevents us from estimating their effect on measures of aggregate economic activity or prices for the relatively short sample for which the Y14 data is available. Intuitively, credit series tend to be quite responsive to changes in interest rates, whereas output and prices tend to be less responsive and influenced by a number of other shocks, which reduces the signal-to-noise in such regressions (see also Nakamura and Steinsson, 2018).

[34]To determine the lag length, we consult the Akaike and Bayesian information criteria. Based on the results, the chosen lag length is a reasonable compromise across outcome variables and impulse response horizons. In unreported results, we find that the results are similar without any controls or four lagged values of both the one-quarter growth rate of the dependent variable and the monetary policy shock.

[35]Compared with the estimates in Figure 1.2, the responses are relatively large: credit lines and term loans jointly rise by around 50 percent to a 100 basis point increase in the two-year government yield. These differences can be explained by (i) the larger size of the shock (a one percentage point increase in the federal funds rate versus the two-year government bond yield), (ii) the fact that the high-frequency shocks come as true surprises whereas the shocks by Romer and Romer (2004) could partly be anticipated, and (iii) that credit lines were less common for the early part of the sample that is used in Figure 1.2 (1970:M1 - 2007:M12). In line with these explanations, Figure A.4 in Appendix A.1 also shows larger responses based on the shock series by Nakamura and Steinsson (2018) for the sample 1994:M1 - 2007:M12.

[36]Another reason why bank-firm credit increases to a monetary tightening is that commercial paper spreads may rise to such an unexpected policy change. In turn, firms may use commercial paper relatively less to meet their short-run liquidity needs and instead draw on their credit lines (Gatev and Strahan, 2006). In Appendix A.2, we provide evidence for such a channel, showing that commercial paper spreads tend to increase after a contractionary monetary policy shock (Figure A.5), while firms also increase their use of commercial paper to satisfy their liquidity needs (Figure A.6). Another relation between credit lines and commercial paper may exist since credit lines can serve as a backup of firms' commercial paper. However, as shown in Table D.3, only around 5.3 percent of committed and 0.4 percent of used credit lines are reported with such a purpose.

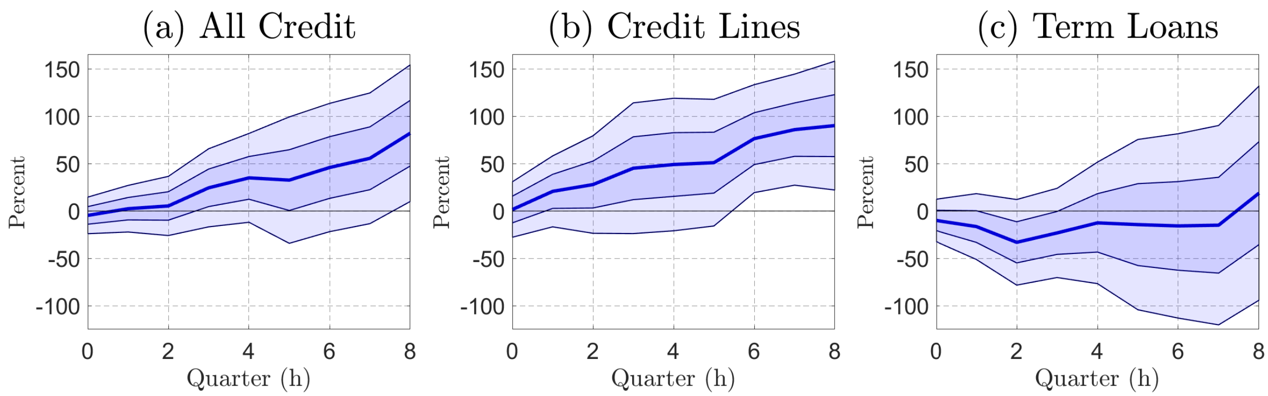


Figure 5.1: Aggregate Credit Responses to a Monetary Policy Surprise.

**Notes:** Impulse responses to a 100 basis point surprise increase in the two-year government bond yield based on the local projection approach in (5.1), multiplied by 100. 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors. Sample: 2012:Q3 - 2019:Q2.

son (2018), shown in Figure E.1, which loads more heavily on the short end of the yield curve compared with the two-year government bond yield (see Figure E.2). In addition, to address the possibility that monetary policy announcements may entail a release of private information of the Federal Reserve (Nakamura and Steinsson, 2018), we follow Jarociński and Karadi (2020) and exclude policy meeting surprises that are associated with nonstandard stock price responses. That is, tightening (easing) surprises that show an increase (decrease) in stock prices at the same time are excluded from the sample.[37] Figure E.2 shows the impulse responses using the refined shock series, which are much the same as the ones in Figure 5.1.

We next update the regression to use the full scope of the micro-data. At the firm-level, we estimate local projections

$$\frac{L_{i,t+h} - L_{i,t-1}}{\overline{L}_{t-1}} = \alpha_i^h + \beta^h \epsilon_t^{MP} + \gamma^h \mathbf{X_{i,t-1}} + u_{i,t}^h \quad , \tag{5.2}$$

where $h = 0, 1, ..., 8$ and $L_{i,t}$ is the amount of some credit type by firm $i$ at time $t$. Note that the dependent variable takes a particular form. The numerator is given by the change in credit of firm $i$ between $t-1$ and $t+h$, while the denominator $\overline{L}_{t-1}$ is the average amount of credit across all firms at $t-1$, that is, $\overline{L}_{t-1} = (1/N)\sum_{i=0}^{N} L_{i,t}$. Given this setup, the estimated coefficients $\beta^h$ are comparable to the ones estimated with aggregate time series in (5.1). As above, we use surprise movements in the two-year government bond yield as a measure of the shock $\epsilon_t^{MP}$, $X_{i,t-1}$ again includes two lagged values of the one-quarter growth rate of the dependent variable and two lags of the monetary policy shock, and $\alpha_i^h$

[37]We use the return of the S&P 500 over the same 30-minute window around policy announcements in this regard. The resulting shock series is shown in Figure E.1 in Appendix E.1.

is a firm-horizon fixed effect.

Estimating 5.2 on the full sample gives the results that are shown in Figure E.3 in Appendix E.1. They are similar to the ones in Figure 5.1, with the difference that the confidence intervals are slightly wider. The additional advantage of the firm-level approach to estimating aggregate impulse responses is that it allows us to decompose the aggregate response by firm characteristics. In particular, we estimate the local projections in (5.2) for credit lines by groups according to their position along the firm size distribution and the borrowing capacity distribution in the quarter before the shock occurs.[38] We separate firms into three groups of similar size and rescale their response by the number of firms in each group relative to the total number of firms for each respective estimation. The results are shown in Figures E.4 and E.5 in Appendix E.1. The total response of credit lines is almost entirely explained by large firms with ex-ante borrowing capacity.[39]

Last, while the positive response of bank-firm credit to a monetary policy tightening may seem counterintuitive, it does not imply that credit supply channels are absent. To illustrate this point, we follow an approach similar to Khwaja and Mian (2008), which is left to Appendix E.2. We construct a data set for firms with multiple banking relationships and show that banks' credit supply response differs depending on their differential exposure to a monetary policy shock. As Gomez et al. (2020), we use the so-called income gap, a measure of the repricing sensitivity of banks' assets and liabilities over the near term, to differentiate banks by their exposure to a monetary policy shock. We find that banks with a larger income gap, that is, more assets relative to liabilities that reprice over the next year, expand credit by more, holding constant firms' credit demand.

## 5.2 Credit Movements during COVID-19

The outbreak of the COVID-19 pandemic and the ensuing period of shelter-in-place and the closure of certain businesses entailed a sharp fall in (expected) cash flows for the majority of firms in the United States. It therefore represents a unique macroeconomic event to study changes in firm credit, in particular because the outbreak was largely unanticipated. In this section, we show that the increase in bank-firm credit that we document in

[38] Firm size is measured by total assets, and borrowing capacity is the amount of unused credit, combining unused credit lines and term loans. In Figure E.5, we consider two versions for firms' borrowing capacity, an unadjusted one, where unused credit is given by the difference between committed credit and used credit, and one that additionally adjusts unused credit for generic covenant rules (see Appendix B.2 for details).

[39] In separate regressions, we confirm that the responses of large firms and the ones with large unused borrowing capacity are also statistically different from the responses of either of the two other groups around the seven-quarter-ahead impulse response horizon at the one standard deviation confidence intervals. Differences in the magnitude of the total responses between Figures 5.1, E.3, E.4, and E.5 may arise because of variations in the sample of firms arising from differences in the data availability that is used in each respective estimation.

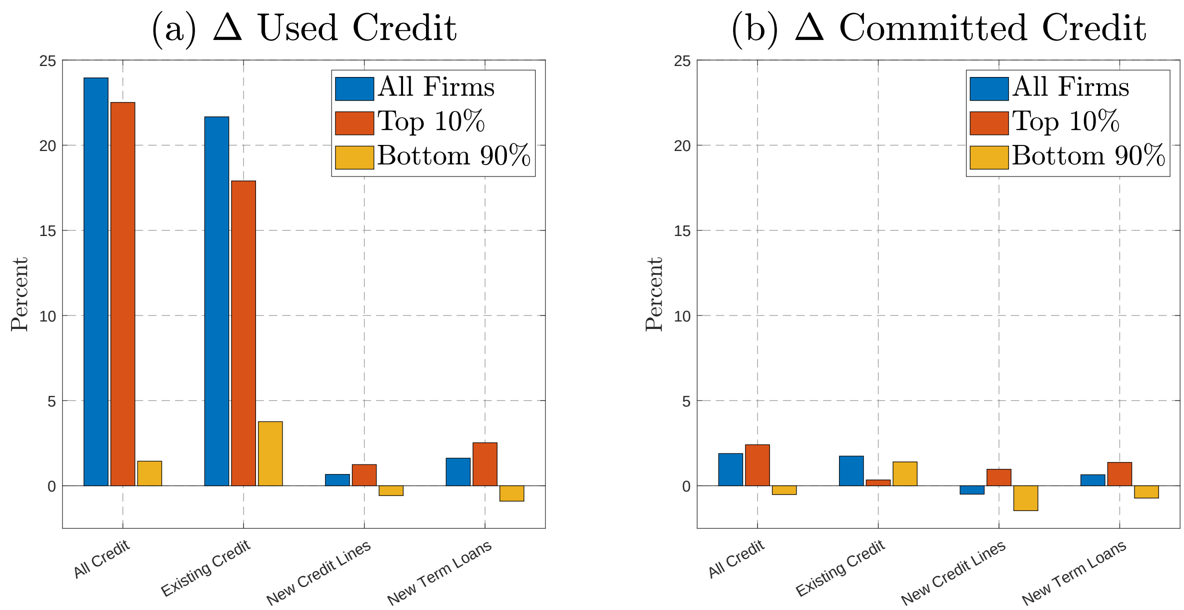


Figure 5.2: Changes in Used and Committed Credit for 2019:Q4 - 2020:Q1.

**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 percent and the bottom 90 percent 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 for the two quarters. See Section 2 and Appendix B for details about the data.

Figure 1.1 in the introduction was mostly accomplished through a higher use of existing credit lines rather than outright new lending. Consistent with the previous findings, the vast majority of the change in credit flowed to large firms with preestablished borrowing capacity.

The COVID-19 orders began to take effect in the United States in mid-March 2020. Comparing end-of-quarter stocks, the points at which the credit variables are measured in the Y14 data, between 2019:Q4 and 2020:Q1 therefore provides an accurate depiction of the immediate changes in credit that likely resulted from the shock and the associated policies. In Figure 5.2, we plot 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 percent and the bottom 90 percent of the firm size distribution (orange and yellow bars), with a cutoff between the two groups of around \$1.5 billion in total assets. That is, 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 type $k$ at time $t$ of group $g$ (all firms, top 10 percent, bottom 90 percent).[40] All changes are scaled by total used bank-firm credit in 2019:Q4 and the quantitative differences relative to Figure 1.1 are due to the alternative scaling by bank total assets.

Panel (a) of Figure 5.2 shows that the overwhelming majority of the change in credit, around 90 percent, is due to an increase in the drawdown of existing credit lines. In contrast, increased issuance of new term loans or new credit lines, while positive, played a minimal role in driving the increase in credit over this period. Breaking down these effects by firm size, we find that nearly all of the additional credit issued over this period flowed to the top 10 percent of the size distribution, with roughly 75 percent explained by the existing credit lines of large firms alone. In contrast, the bottom 90 percent of firms saw a moderate increase in credit from existing lines, as well as small decreases in the issuance of new lines and loans.[41]

Panel (b) of Figure 5.2 shows changes in committed, rather than used, credit. In aggregate, committed credit barely increased over this period, showing that credit growth was nearly entirely explained by increased utilization of existing lines, rather than increases in credit line limits. But, while the largest 10 percent of firms were able to slightly increase the balances of committed credit, the bottom 90 percent displayed a drop originating from new term loans and credit lines.

Figure E.7 in Appendix E.3 repeats these calculations for the sample 2019:Q4 - 2020:Q2. While more than half of the increase of used existing credit in 2020:Q1 tapers off in 2020:Q2, the change for the bottom 90 percent of firms actually turns negative for the two-quarter comparison and the one for the top 10 percent remains elevated. Similar heterogeneity is present for new credit issuances. These distributional differences could become even more stark in a prolonged downturn.[42]

[40] The firm size distribution for both quarters is computed according to firms' total assets in 2019:Q4, such 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 percent or the bottom 90 percent according to the share of each group of total credit across nonmissing observations.

[41] Separating the change in existing credit by industry, Figure E.9 in Appendix E.3 shows that "Manufacturing" accounted for the largest share of the aggregate change, whereas "Accommodation and Food Services" drew the most credit relative to its unused credit in 2019:Q4.

[42] In Appendix E.3, we provide further evidence for credit shifting toward less financially constrained firms. The type of firms that accessed their credit lines in 2020:Q1 changed compared to "normal times": large, profitable, publicly traded firms with preestablished borrowing capacity draw on their available funding (see also Chodorow-Reich et al., 2020). We document similar patterns for new credit issuances. As a result, we find that the share of credit secured by some form of collateral, weighted by the used amount, actually decreased on credit lines between 2019:Q4 and 2020:Q1, from around 0.78 to 0.7 for existing credit lines and from 0.82 to 0.58 for new credit lines.

## 5.3 Credit Supply during COVID-19

While these patterns indicate that access to credit differed in the cross-section of firms, they do not distinguish between credit demand and supply, and possible spillovers between 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 smaller firms. We test for such crowding out effects by employing a fixed effect regression similar to Khwaja and Mian (2008). The methodology for estimating a credit supply channel focuses on firms borrowing from multiple banks, where banks differ in their exposure to the outbreak of COVID-19. As a measure of banks' exposure, we use differences of withdrawals on existing credit lines across banks.

The approach relies on two key identifying assumptions. First, the shock must be exogenous, an assumption that we believe is satisfied, since 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 would, for example, be violated if firms change their demand for term loans because they alter their use of credit lines at some bank. One possible reason for such a relation is that credit lines often have predetermined interest rates, such that they may become relatively cheaper when the general cost of credit increases. To ensure that the second identifying assumption is satisfied, we restrict the data to term loans only, and exclude relations between a bank and a firm that not only cover term loans but also credit lines, such that the results cannot be driven by a possible interaction between the two at some bank.[43] Based on the restricted data set, we estimate

$$\frac{L^{j,k}_{i,t+h} - L^{j,k}_{i,t-1}}{0.5\left(L^{j,k}_{i,t+h} + L^{j,k}_{i,t-1}\right)} = \alpha^k_i + \beta\,\frac{\Delta Credit\ Line\ Usage^j_t}{Assets^j_{t-1}} + \gamma_1 \frac{\Delta Deposits^j_t}{Assets^j_{t-1}} + \gamma_2 X^j_{t-1} + u^{j,k}_i\,, \quad (5.3)$$

for $h = 0, 1$, where $t-1$ denotes 2019:Q4 and $t+h$ is either given by 2020:Q1 or 2020:Q2. For the dependent variable, we use the same formulation as in Section 4.2, which allows for possible zero-observations in $t-1$ or $t+h$ and is bounded in the range $[-2, 2]$. $L^{j,k}_{i,t}$ is the loan amount of type $k$ between bank $j$ and firm $i$ at time $t$, where $k$ denotes either fixed- or variable-rate term loans.[44] The firm-specific fixed effect $\alpha^k_i$ absorbs a firm's common demand for credit type $k$. The estimated coefficient $\beta$ associated with the change of

[43] Similarly, firms' demand for credit line withdrawls and term borrowing should not be influenced by worries about bank insolvency, which may give rise to a correlation between drawdowns and term lending. However, such identification concerns are unlikely to be important, since bankruptcy risk was not a significant concern over our sample period and by 2020:Q2, none of the banks in our sample declared insolvency.

[44] We consider variable- and fixed-rate loans as separate types to account for possible differences in the cost and demand for such loans due to changes in short-term interest rates between $t-1$ and $t$.

used existing credit lines between $t-1$ and $t$ at bank $j$, relative to total assets in $t-1$, therefore captures credit supply effects: banks may differ in their supply of term loans, given by their differential intensity of credit line withdrawals.[45] The remaining regressors are omitted in the baseline specification and added subsequently to test the robustness of the results.

The estimation results for regression (5.3) are shown in Table 5.1. Column (i) shows the results for used term loans between 2019:Q4 and 2020:Q1. The negative sign of the coefficient $\beta$ implies that a bank that experiences a larger drawdown of credit lines restricts its supply of term loans by more.[46] In column (ii), we extend the fixed effect to cover not only loan types according to the flexibility of their interest rate but also by their remaining maturity.[47] This extension checks the robustness of the results for the possibility that the amount of credit line drawdowns and the maturity profile of a bank's term loan portfolio are correlated, and a firm's credit demand depends on the remaining maturity (see also Khwaja and Mian, 2008). If anything, the results become stronger with the extended fixed 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, Rappoport and Schnabl, 2020). For bank specialization to explain our results, banks would have to hedge their lending activities across loan types, such that banks with larger credit line drawdowns specialize in providing term loans that are less likely to be associated with firms' short-run liquidity needs. To address this concern, we additionally allow for the firm fixed effect in regression (5.3) to vary with the loan purpose that firms report.[48] To account for other pre-crisis differences across banks, we also include various bank-specific controls that are collected in the vector $X_{t-1}^{j}$: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total liabilities), and

[45]To a large extent, drawdowns on existing credit lines cannot be influenced by banks which have to honor such precommitments. In some cases, banks can decline firms' requests for drawdowns, for example, when covenants are violated. If banks use such partial discretion more when their own balance sheets are impaired, then the estimated effects in Table 5.1 can be seen as a lower bound in absolute terms.

[46]Besides these quantity responses, we also test for price responses using the change in the interest rate, weighted by used term loans, as a dependent variable in (5.3). As Khwaja and Mian (2008), we find that the estimated coefficient $\beta$ is insignificant at standard confidence levels, showing that the identified credit supply channel rather operates through quantity adjustments than price changes.

[47]In particular, we split loans into three maturity buckets according to their remaining maturity in 2019:Q4: (i) less than one quarter, (ii) less than one year, and (iii) more than one year. We do not estimate separate regressions for maturing loans or new loans but rather include all loans into the estimations since loan contracts are often renewed or renegotiated over their lifetime, partly due to covenant violations by firms.

[48]Specifically, we distinguish between the purposes "Working Capital," "Capital Expenditures" (including real estate), "M&A Financing," and "All Other Purposes."

Table 5.1: COVID-19 — Credit Supply.

| | (i) 2020:Q1 | (ii) 2020:Q1 | (iii) 2020:Q1 | (iv) 2020:Q1 | (v) 2020:Q2 |
|---|---|---|---|---|---|
| Δ Credit Line Usage | -2.00*** | -2.23*** | -2.66*** | -1.74** | -2.60** |
| | (0.66) | (0.64) | (0.87) | (0.63) | (1.02) |
| Δ Deposits | | | | 0.14 | |
| | | | | (0.20) | |
| Fixed Effects | | | | | |
| Firm × Rate | ✓ | | | ✓ | ✓ |
| Firm × Rate × Maturity | | ✓ | | | |
| Firm × Rate × Purpose | | | ✓ | | |
| Bank Controls | | | ✓ | ✓ | |
| R-squared | 0.51 | 0.51 | 0.55 | 0.51 | 0.51 |
| Observations | 1,677 | 1,597 | 1,003 | 1,637 | 1,490 |
| Number of Firms | 748 | 712 | 462 | 732 | 670 |
| Number of Banks | 28 | 28 | 26 | 26 | 28 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q1 in columns (i)-(iv) and from 2019:Q4 to 2020:Q2 in column (v). 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). 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 liabilities), and banks' income gap (see Table B.5 in Appendix 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

banks' income gap (see Table B.5 in Appendix B.1 for details on the data).[49] Column (iii) in Table 5.1 shows that the results actually intensify with the extended fixed effect and the additional control variables.

These spillover effects are perhaps surprising given that the Federal Reserve instantly provided liquidity to financial markets following the COVID-19 outbreak and aggregate bank deposits increased by more than C&I loans over this period (see Figure 1.1 in the introduction). Moreover, banks are known to match the cyclicality of their deposit flows and credit line draws, as pointed out in Gatev and Strahan (2006). Taken together, this implies that banks should have had more than sufficient funding to cover their credit line draws without contracting their other lending activity. Instead, we find strong evidence of a credit crunch in the market for term loans despite the available liquidity.

To isolate the role of deposits, we modify the baseline specification and additionally

[49] 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.

control for the deposit inflow in the first quarter of 2020, denoted by $\Delta Deposits_t^j / Assets_{t-1}^j$ in regressions (5.3), as well as various other bank characteristics collected in $X_{t-1}^j$.[50] Column (iv) in Table 5.1 shows the estimation results. Despite the additional controls, the estimated coefficient $\beta$ remains nearly unchanged compared with the baseline in column (i). At the same time, we find a coefficient of close to zero on the change in deposits, and can easily reject the hypothesis $\gamma_1 + \beta = 0$. In other words, our estimates imply that the combination of an inflow to a bank of \$1 of deposits, paired with a simultaneous outflow of \$1 on a drawn credit line, is not neutral, but instead causes a significant decrease in that bank's supply of term loans. This lack of equivalence between deposit inflows and credit line outflows can in turn explain our findings of a term loan crunch in an environment of plentiful deposits.[51,52]

We interpret these results as providing strong evidence that banks were facing important costs or constraints on lending besides the direct availability of funds in the weeks following the outbreak of the pandemic.[53] While not necessarily immediately binding, banks were likely expecting to be confronted by either market-based or regulatory constraints, and were therefore trying to avoid additional risk on their balance sheets, leading to a trade-off between honoring credit lines and term lending.[54] Aware of the pressure

[50]The regressors of interest in equation (5.3) show substantial variation across banks: the drawdown on existing credit lines relative to lagged assets ranges from -0.2 to around 3.6 percent with a standard deviation of around 1 percent, and the change in deposits relative to lagged assets ranges from 0.9 percent to around 31 percent with a standard deviation of around 6.7 percent. The two variables are negatively correlated with a correlation coefficient of -0.16, 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. In addition, using weekly deposit rate data from Ratewatch and weekly balance sheet data for U.S. commercial banks from the FR-2644 forms, we find no evidence that banks that paid higher deposit rates attracted more deposits over the period that is shown in Figure 1.1 from 2/12/2020 to 4/8/2020 (results not reported), suggesting that the deposit inflow was not strongly influenced by individual bank decisions.

[51]Nonetheless, the large deposit inflow likely helped banks to honor the drawdowns on their existing credit lines (Li, Strahan and Zhang, 2020). As shown in Figure 1.1, bank deposits increased by more than C&I loans following the outbreak of COVID-19. In the cross-section, we find that this pattern also holds for all banks in the Y14 data which show a stronger increase in deposits relative to the drawdown of existing credit lines. However, apart from these large BHCs, the underlying micro-data of the aggregate H.8 releases that are used in Figure 1.1 also show that such a surplus of deposits does not apply equally to all banks. In Figure E.8 in Appendix E.3, we document that a substantial fraction of banks experienced a larger increase in C&I loans than deposits. Hence, smaller banks were potentially more constrained in 2020:Q1.

[52]Consistent with these results, cash-assets of U.S. commercial banks increased by around one trillion U.S. dollars over the period that is shown in Figure 1.1 (3/11/2020-4/8/2020), or around 5 percent relative to total assets on 3/11/2020 (Source: H.8 releases for U.S. commercial banks).

[53]Credit line drawdowns can easily tighten banks' regulatory capital or increase their leverage ratios. For example, the undrawn balances on credit lines typically have smaller regulatory risk weights than drawn balances. 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 percent, while exposures with maturities over one year receive a 50 percent CCF. If the commitment can be unconditionally canceled at any time, the exposure receives a zero percent CCF, or a zero-risk weighting. Details can be found at: https://www.bis.org/basel_framework/

[54]To test whether regulatory constraints can explain our results, we consider alternative specifications

on banks' balance sheets, policy-makers provided liquidity to financial markets through various channels and eased restrictions on banks, with some of the regulatory changes taking place within our estimation sample.[55] While our findings can be understood as a rationale for such interventions, they also show that the policy actions did not completely offset the pressure from credit line drawdowns on bank balance sheets.

The crowding out effects that we uncover are potentially a smaller concern if they are only present immediately after the start of a crisis and are relatively short-lived. To test for the persistence of the results, we consider changes in the dependent variable from 2019:Q4 to 2020:Q2 in regressions (5.3). As shown in column (v) of Table 5.1, the effects not only remain but actually intensify at the end of 2020:Q2, a finding that is robust to various modifications of the regression specification as shown in Table E.3 in Appendix E.3. The size of the coefficients for both quarters also suggest that the effects are economically important: given the average ratio of term lending to bank assets that we observe, these estimates imply a credit supply contraction of around 10-20 cents for a $1 drawdown of credit lines. A substantial spillover effect but likely a lower bound of the total crowding out effect. First, we do not observe small firm lending below $1 million in committed amount. Second, the credit supply contraction likely extends to consumer and real estate credit, which are not part of our analysis.

### 5.3.1 Further Evidence and Robustness

We provide further evidence and test the robustness of our findings in several ways, and the related estimation results are left to Appendix E.3. First, the identification approach requires firms to borrow from multiple banks, potentially restricting the sample to larger firms that could find alternative sources of funding more easily elsewhere. To investigate which type of borrowing drives our results, we split the sample along various dimensions and the results are shown in Tables E.4 and E.5. Our findings are largely explained by a suply contraction of smaller, fixed-rate, and non-syndicated loans - characteristics that are all more prevalent among SMEs which therefore faced a sharper lending cut.[56]

Second, Table E.6 shows the results for specifications that leave out the firm fixed

of regression (5.3) that allow for interactions between the credit line drawdowns and bank capital ratios in 2019:Q4. We find only weak evidence that banks with lower pre-crisis capital ratios restricted term lending by more to a drawdown on existing credit lines. However, regulatory constraints can still explain our findings, if such constraints affected all banks similarly or banks were worried about the possibility of facing a regulatory constraint in the future, relative to their pre-crisis capital ratios that were chosen optimally.

[55] For an overview of the bank regulatory policy actions, see, e.g., Blank, Stein, Hanson and Sunderam (2020).

[56] Missing observations of firm financials result in small samples and prevent us from splitting the data according to measures of firm size such as total assets. For the same reason, we do not estimate how the credit responses translate into real outcomes, such as firm investment or employment (see, e.g., Chodorow-Reich, 2014; Huber, 2018).

effect $\alpha_i^k$ in regressions (5.3) and extend the data to include single bank-firm relations. The estimated coefficients $\hat{\beta}$ are smaller compared with the one in column (i) of Table 5.1, highlighting the importance of controlling for firm credit demand and a data set of firms with multiple bank-relationships, while at the same time confirming the sign and significance of our result. The results even remain when considering firms with a single lender in our data, a subset of firms that includes the smallest ones that are observed.

Last, a potential identification concern with regressions (5.3) is that banks may have restricted their term lending through an alternative channel than the one associated with credit line drawdowns and such a channel is not fully captured by the bank controls in columns (iii) and (iv) in Table 5.1. In particular, banks with larger credit line drawdowns may have also experienced a stronger decline in the profitability of their legacy loans and such banks could have restricted their term lending because of that. To address this concern, we follow two approaches. First, we use an instrumental variable estimation for regression (5.3). As an instrument for the credit line drawdowns, we use 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. The results are shown in Table E.7 in Appendix E.3. Again, for both the one-quarter and the two-quarter changes of the dependent variable, we obtain similar results that are larger in absolute magnitude for non-syndicated loans. Second, we directly control for the change in the quality of a bank's existing term loan portfolio using the banks' own reported risk assessments measured by changes in the probability of default. Additionally, we include changes in the provision for loan losses reported in banks' income statement as a control variable. The results, reported in Table E.8, remain much the same.

# 6 Model

This section derives a theoretical model to study the general equilibrium implications of the credit line channel for firm borrowing and investment. We briefly summarize the key ingredients of the model, present the detailed model structure, calibrate the model, and finally describe our findings.

## 6.1 Model Overview

Our model is designed to capture the main features of the empirical patterns we document. To account for heterogeneity in credit line access in a tractable way, we allow for two types of firms: constrained firms that face a binding lower limit on their dividend payouts, and unconstrained firms that do not. Inspired by our empirical findings, the unconstrained firms borrow using credit lines, while the constrained firms borrow using term loans.

To introduce credit lines in a parsimonious manner, we make the simple assumption that term loans are priced at the market-clearing rate, while credit lines always have a fixed, predetermined spread over the risk-free interest rate. Lenders face convex funding costs for providing either form of credit, implying that spreads increase with the quantity of credit demanded. As a result, borrowing by one type of firm (i.e., unconstrained firms drawing on credit lines) can crowd out credit supply for the other firms in the economy.

To discipline debt accumulation, we impose debt-to-EBITDA covenants that are costly to violate following Greenwald (2019). Firms face idiosyncratic risk, leading them to reduce their probability of violation by keeping a precautionary buffer between their debt-to-EBITDA ratio and the covenant threshold. This specification both matches the findings by Sufi (2009) that firms with credit lines are typically limited by their covenants rather than the amount of committed credit, and also realistically ensures that firms are not literally constrained from obtaining more credit at equilibrium, but instead choose not to do so to reduce the expected costs of violation and distress.

We embed this financial structure into a macroeconomic environment with dividend smoothing incentives and capital adjustment costs. This structure implies that, following an adverse shock, firms must balance the drop in available resources among three costly margins: reducing dividends, which impairs smoothing; reducing investment, which incurs adjustment costs; or increasing debt, which increases covenant violation risk. At equilibrium, the more flexible dividend margin for the unconstrained firms will make their credit demand more sensitive to spreads, a key driver of our results.

## 6.2 Model Structure

**Demographics and Preferences.** The economy is made up of three types of households: unconstrained entrepreneurs (denoted $U$), constrained entrepreneurs (denoted $C$), and savers (denoted $S$). Each type has access to a complete set of contracts that can be traded among other agents of that type, but not across types. This allows for complete insurance within each type, yielding aggregation. The entrepreneur types have preferences over nondurable consumption $C_{j,t}$ given by

$$U_{j,t} = E_t \sum_{k=0}^{\infty} \beta_j^k u(C_{j,t+k}) \tag{6.1}$$

$$u_j(C_{j,t}) = \frac{C_{j,t}^{1-\psi_j}}{1-\psi_j} \tag{6.2}$$

for $j \in \{U, C\}$. The saver type has preferences over nondurable consumption $C_{S,t}$ and labor hours $N_{S,t}$ given by

$$U_{S,t} = E_t \sum_{k=0}^{\infty} \beta_S^k u_S(C_{S,t+k}, N_{S,t+k}) \tag{6.3}$$

$$u_S(C_{S,t}, N_{S,t}) = \frac{C_{S,t}^{1-\psi_S}}{1-\psi_S} - \chi \frac{N_{S,t}^{1+\varphi}}{1+\varphi}. \tag{6.4}$$

Following Herreño (2020), we compute total labor supply as a CES aggregate of labor supplied to the constrained and unconstrained sectors, so that

$$N_{S,t} = \left[ a_U N_{U,t}^{\frac{\epsilon_n - 1}{\epsilon_n}} + a_C N_{C,t}^{\frac{\epsilon_n - 1}{\epsilon_n}} \right]^{\frac{\epsilon_n}{\epsilon_n - 1}}.$$

This functional form allows us to separately control the elasticity of aggregate labor supply and the flexibility of shifting labor across the two sectors.

**Productive Technology and Labor Demand.** Each entrepreneur owns a firm, which we index with $j \in \{U, C\}$ after the owner. The production function for firm $i$ of type $j$ is

$$Y_{i,j,t} = Z_t \left( \omega_{i,j,t} K_{i,j,t-1} \right)^{\alpha} N_{i,j,t}^{1-\alpha}$$

where aggregative productivity $Z_t$ follows an AR(1) in logs

$$\log Z_t = (1 - \rho_Z) \log \bar{Z} + \rho_Z \log Z_{t-1} + \varepsilon_{Z,t}, \qquad \varepsilon_{Z,t} \sim N(0, \sigma_Z^2)$$

and represents the only source of aggregate risk in the economy. The term $\omega_{i,j,t}$ is a permanent shock to the quality of the firm's capital drawn i.i.d. across firms and time with $E[\omega_{i,j,t}] = 1$. Given its choice of capital $K_{i,j,t-1}$ and capital quality shock $\omega_{i,j,t}$, each firm chooses its labor demand to maximize its EBITDA

$$X_{i,j,t} = \left[ P_{j,t} Z_t n_{i,j,t}^{1-\alpha} - w_t n_{i,j,t} \right] \left( \omega_{i,j,t} K_{i,j,t-1} \right)$$

where $P_{j,t}$ is the relative price of the intermediate good produced by sector $j$, and $n_{i,j,t} \equiv N_{i,j,t} / \left( \omega_{i,j,t} K_{i,j,t-1} \right)$ is the firm's choice of labor intensity.[57] The optimality condition is

$$(1 - \alpha) P_{j,t} Z_t n_{i,j,t}^{-\alpha} = w_t$$

[57] This is not an assumption but rather a simple result of profit maximization, since the firm's problem depends only on labor demand to the extent that it affects EBITDA.

implying a symmetric solution $n_{j,t}$ across all firms of type $j$. Substituting, we find that, at equilibrium, firm EBITDA is given by

$$X_{i,j,t} = x_{j,t}\omega_{i,j,t}K_{i,j,t-1}$$
$$x_{j,t} \equiv P_{j,t}Z_t n_{j,t}^{1-\alpha} - w_t n_{j,t}.$$

**Debt Contracts.** Firms borrow in the form of one-period risk-free debt. Unconstrained firms borrow using credit lines at interest rate $r_{U,t}$, while constrained forms borrow in the form of term loans at interest rate $r_{C,t}$. There is no difference between these debt contracts other than the relevant interest rate. Specifically, credit lines always pay a fixed spread $\bar{s}_U$ over the short-term interest rate $r_t$, while term loans have a potentially time-varying spread that is determined to clear the market.

**Debt Covenants.** Both loan types contain covenants that require the firm to pay a penalty if its debt $L_{i,j,t}$ exceeds a threshold $\bar{L}_{i,j,t}$ that is a function of the firm's financial ratios. We model $\bar{L}$ as a debt-to-EBITDA limit, implying that $\bar{L}$ should be proportional to EBITDA. In practice, debt-to-EBITDA ratios are computed using a smoothed value for EBITDA, usually the average over the last four quarters. We therefore define

$$\bar{L}_{i,j,t} = \theta\mathcal{X}_{j,t}\omega_{i,j,t}K_{i,j,t-1}, \qquad \mathcal{X}_{j,t} \equiv (1-\rho)\sum_{k=0}^{\infty}\rho^k x_{j,t-k}$$

where $\theta$ is the maximum allowed debt-to-EBITDA ratio.[58] Assuming a symmetric solution, we can write

$$\bar{L}_{i,j,t} = \omega_{i,j,t}\bar{L}_{j,t}, \qquad \bar{L}_{j,t} \equiv \theta\mathcal{X}_{j,t}K_{j,t-1}.$$

The firm violates its covenant if its nominal debt exceeds this value, which again assuming a symmetric solution is equivalent to

$$\bar{\pi}^{-1}L_{j,t-1} > \omega_{i,j,t}\bar{L}_{j,t},$$

where $\bar{\pi}$ is inflation, which is constant in our model. Such a violation occurs if $\omega_{i,j,t} < \bar{\omega}_{j,t}$, where

$$\bar{\omega}_{j,t} = \frac{\bar{\pi}^{-1}L_{j,t-1}}{\bar{L}_{j,t}}.$$

[58]To maintain tractability, we consider a functional form in which violation is based only on the current realization of $\omega_{i,j,t}$ and not on past values of these idiosyncratic shocks.

Expected violation costs per unit of debt are therefore equal to

$$\xi_{j,t} \equiv \kappa \Gamma_\omega(\bar{\omega}_{j,t}),$$

which is the product of $\kappa$, the proportional fee conditional on violation, and $\Gamma_\omega(\bar{\omega}_{j,t})$, the probability of violation.

**Firms.** Each member of an entrepreneur family owns a firm. Each firm $i$ of type $j \in \{U, C\}$ uses capital and labor to produce, and maximizes the present value of dividends to the entrepreneur household of type $j$,

$$V_{i,j,t} = \max D_{i,j,t} + E_t\Big[\Lambda_{j,t+1} V_{i,j,t+1}\Big], \tag{6.5}$$

where $D_{i,j,t}$ are dividends, and $\Lambda_{j,t+1}$ is the stochastic discount factor of the type $j$ entrepreneur

$$\Lambda_{j,t+1} = \beta_j \left(\frac{C_{j,t+1}}{C_{j,t}}\right)^{-\psi_j}.$$

The budget constraint for firm $i$ of type $j$ is

$$\begin{aligned} D_{i,j,t} \leq \Big[(1-\tau)x_{j,t} + \Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t}\Big]\omega_{i,j,t}K_{i,j,t-1} \\ - \bar{\pi}^{-1}\Big(1+(1-\tau)r_{j,t-1} + \kappa\mathcal{I}_{i,j,t}\Big)L_{i,j,t-1} - Q_{j,t}K_{i,j,t} + L_{i,j,t} \end{aligned} \tag{6.6}$$

where $\tau$ is the corporate tax rate, $\delta$ is the depreciation rate, $\bar{Q}_{j,t}$ is the resale price of old capital, $Q_{j,t}$ is the price of new capital, $\bar{\pi}$ is the inflation rate, $L_{i,j,t}$ is the quantity of debt a firm takes on, $r_{j,t}$ is the interest rate on that debt, and $\mathcal{I}_{i,j,t}$ is an indicator for whether the firm violates its covenant. We realistically assume that both depreciation and interest payments on debt are tax-deductible by the firm.

Each entrepreneur family insures its members' firms against realizations of $\omega_{i,j,t}$, allowing for aggregation, and implying the symmetric solution $K_{i,j,t} = K_{j,t}$ and $L_{i,j,t} = L_{j,t}$. Integrating (6.6) over the realizations of $\omega_{i,j,t}$ yields the representative firm budget constraint

$$\begin{aligned} D_{j,t} \leq \underbrace{\Big[(1-\tau)x_{j,t} + \Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t}\Big]}_{\text{return to capital}} K_{j,t-1} \\ - \underbrace{\bar{\pi}^{-1}\Big(1+(1-\tau)r_{j,t-1} + \xi_{j,t}\Big)L_{j,t-1}}_{\text{payment on existing debt}} - \underbrace{Q_{j,t}K_{j,t}}_{\text{new capital}} + \underbrace{L_{j,t}}_{\text{new debt}}. \end{aligned} \tag{6.7}$$

**Payout Constraints.** Following Bernanke, Gertler and Gilchrist (1999), we use a combination of firm exit and a constraint on non-negative dividends for surviving firms, to generate a sector of constrained firms. We assume that firms exogenously exit the market at rate $1-\gamma_j$ each period, at which point they must pay out their available resources as a dividend. For intraperiod timing, the exit occurs after production and repayment of debt, but before the firm's choices of new debt and capital. Non-exiting firms face a payout constraint implying that dividends cannot be negative. Aggregating over exiting and surviving firms, we obtain the minimum payout constraint

$$\begin{aligned} D_{j,t} \geq (1-\gamma_j)\Big\{ \Big[(1-\tau)x_{j,t} + \Big(1-(1-\tau)\delta\Big)\bar{Q}_t\Big] K_{j,t-1} \\ - \bar{\pi}^{-1}\Big(1+(1-\tau)r_{j,t-1} + \xi_{j,t}\Big) L_{j,t-1}\Big\}. \end{aligned} \tag{6.8}$$

The key difference between the constrained and unconstrained sectors are their survival rates $\gamma_j$. We assume that the constrained sector has a lower survival rate, which causes (6.8) to bind at equilibrium. In contrast, the unconstrained sector has a higher survival rate, which leads (6.8) to be slack. Intuitively, the lower required payout rate allows the unconstrained firms to accumulate enough capital to outgrow the constraint. At equilibrium, (6.8) therefore implies that the constrained sector devotes a larger share of its resources to payouts, which is perhaps counterintuitive. We note, however, that *surviving* firms in this sector face a binding minimum of zero dividends, consistent with the empirical evidence on constrained firms in, e.g., Cloyne et al. (2019).[59]

To examine the implications of this constraint on firm debt and investment, we can combine (6.7) and (6.8) to obtain

$$\begin{aligned} Q_{j,t}K_{j,t} \leq \gamma_j\Big\{ \Big[(1-\tau)x_{j,t} + \Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t}\Big] K_{j,t-1} \\ - \bar{\pi}^{-1}\Big(1+(1-\tau)r_{j,t-1} + \xi_{j,t}\Big) L_{j,t-1}\Big\} + L_{j,t}. \end{aligned} \tag{6.9}$$

Equation (6.9) shows that when the payout constraint binds, firm investment moves one-for-one with new debt financing $L_{j,t}$. As a result, constrained firms have a much higher marginal propensity to invest out of debt than unconstrained firms at equilibrium.

**Government Sector.** The monetary authority targets and achieves a constant inflation rate $\bar{\pi}$, while the fiscal authority spends corporate tax revenues on government spending $G_t$ that has no effect on household utility.

[59] Even though many firms pay zero dividends, the constrained entrepreneur who prices the firms' cash flows still has nonzero consumption at equilibrium due to the payouts of exiting firms, implying that paying zero dividends can be optimal even when entrepeneur utility is concave.

**Entrepeneurs' Problems.** The unconstrained and constrained entrepreneurs simply choose consumption $C_{j,t}$ to maximize (6.1) subject to the budget constraint $C_{j,t} \leq D_{j,t}$.

**Firm's Problem.** The representative firm of type $j \in \{U, C\}$ maximizes (6.5) subject to (6.7) and (6.9). The optimality condition for capital is

$$(1+\mu_{j,t})Q_{j,t} = E_t\left\{\Lambda_{j,t+1}\left[(1+\gamma_j\mu_{j,t+1})\Big((1-\tau)x_{j,t+1} + (1-\delta)\bar{Q}_{t+1}\Big) + \Psi_{j,t+1}\frac{\partial \bar{L}_{j,t+1}}{\partial K_{j,t}}\right]\right\}$$

where

$$\Psi_{j,t} = -(1+\gamma\mu_{j,t})\bar{\pi}^{-1}L_{j,t}\frac{\partial \xi_{j,t}}{\partial \bar{L}_{j,t}} + E_t\left\{\Lambda_{j,t+1}\Psi_{j,t+1}\frac{\partial \bar{L}_{j,t+1}}{\partial \bar{L}_{j,t}}\right\}$$

and where $\mu_{j,t}$ is the multiplier on the payout constraint (6.8). The condition for debt is

$$1+\mu_{j,t} = E_t\left\{\Lambda_{j,t+1}\bar{\pi}^{-1}(1+\gamma\mu_{j,t+1})\left[\Big(1+(1-\tau)r_t + \xi_{j,t+1}\Big) + \frac{\partial \xi_{j,t+1}}{\partial L_{j,t}}L_{j,t}\right]\right\}.$$

**Saver's Problem.** The saver chooses consumption $C_{S,t}$, labor $N_{S,t}$, and the quantity of credit $L_{S,t}$ to maximize (6.3) subject to the budget constraint

$$C_{S,t} \leq w_t N_{S,t} + \sum_{j\in\{U,C\}} \underbrace{\left\{\bar{\pi}^{-1}\left(1+r_{j,t-1}\right)L_{j,t-1} - L_{j,t}\right\}}_{\text{net lending income}} - \underbrace{(1+\zeta_L)^{-1}\eta\left(\frac{L_{U,t}+L_{C,t}}{L_U+L_C}\right)^{1+\zeta_L}}_{\text{holding cost}}$$
$$+\underbrace{(1+r_{t-1})\bar{\pi}^{-1}A_{t-1} - A_t}_{\text{bonds}} + \underbrace{T_{S,t}}_{\text{rebate}}.$$

where $A_t$ are risk-free bonds in zero net supply, and where $L_U$ and $L_C$ are the steady-state versions of $L_{U,t}$ and $L_{C,t}$, respectively. The holding cost in the term above results in a credit supply curve with arbitrary elasticity and is rebated lump sum to savers in the form of $T_{S,t}$. The saver's optimality condition for labor is

$$\chi N_{S,t}^{\varphi} = C_{S,t}^{-\psi_S} w_t$$

while the optimality condition for bonds is

$$1+r_t = E_t\Big[\Lambda_{S,t+1}\bar{\pi}^{-1}\Big]^{-1}. \tag{6.10}$$

where $\Lambda_{S,t+1}$ is the saver's stochastic discount factor

$$\Lambda_{S,t+1} = \beta_S \left( \frac{C_{S,t+1}}{C_{S,t}} \right)^{-\psi_S}$$

The interest rate on term loans $r_{C,t}$ must satisfy the saver's optimality condition for $L_{C,t}$:

$$1 + \eta \left( \frac{L_{U,t} + L_{C,t}}{L_U + L_C} \right)^{\zeta_L} = (1 + r_{j,t}) E_t \left\{ \Lambda_{S,t+1} \bar{\pi}^{-1} \right\}.$$

Substituting from (6.10) we obtain

$$(1 + r_{C,t}) = (1 + r_t)(1 + s_{C,t}), \qquad s_{C,t} \equiv \eta \left( \frac{L_{U,t} + L_{C,t}}{L_U + L_C} \right)^{\zeta_L}.$$

in each period, where $s_{C,t}$ is the markup on the loan relative to a risk-free bond. Under credit lines, the key feature of the model is that the saver does not choose the amount of credit line lending $L_{U,t}$ but instead has promised to provide this credit at a prespecified rate

$$(1 + r_{U,t}) = (1 + r_t)(1 + \bar{s}_U).$$

where $\bar{s}_U$ is a constant markup or spread. As a result, credit lines have more favorable pricing than term loans if and only if $\bar{s}_U < s_{C,t}$.

**Capital Producers.** Competitive producers create the capital for each sector using the production 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 $j$. The capital producers buy existing capital at price $\bar{Q}_{j,t}$ and sell new capital at price $Q_{j,t}$. Therefore, the capital producer's problem is given by

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

The optimality conditions are

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

where $i_{j,t} \equiv I_{j,t}/K_{j,t-1}$.[60]

**Final Good Producers.** The intermediate goods from each sector are packaged by competitive final goods producers using the technology

$$Y_t = \left[ a_U Y_{U,t}^{\frac{\epsilon_y - 1}{\epsilon_y}} + a_C Y_{C,t}^{\frac{\epsilon_y - 1}{\epsilon_y}} \right]^{\frac{\epsilon_y}{\epsilon_y - 1}}.$$

The price of the final good is normalized to unity, while the prices of the intermediate goods are $P_{j,t}$ for $j \in \{U, C\}$. Combining, the final good producer's problem is

$$\max_{Y_{U,t}, Y_{C,t}} \left[ a_U Y_{U,t}^{\frac{\epsilon_y - 1}{\epsilon_y}} + a_C Y_{C,t}^{\frac{\epsilon_y - 1}{\epsilon_y}} \right]^{\frac{\epsilon_y}{\epsilon_y - 1}} - P_{U,t} Y_{U,t} - P_{C,t} Y_{C,t}.$$

The optimality conditions are

$$P_{j,t} = a_j \left( \frac{Y_{j,t}}{Y_t} \right)^{-\frac{1}{\epsilon_y}}$$

which pin down the relative prices of the goods.

**Equilbrium.** Competitive equilibrium in this model is a allocation of endogenous states $(K_{j,t}, L_{j,t}, \bar{L}_{j,t}, r_{j,t})$ for $j \in \{U, C\}$, policies $(n_{U,t}, n_{C,t}, n_{S,t}, i_{U,t}, i_{C,t})$, and prices $(\mu_{U,t}, \mu_{C,t}, r_{U,t}, r_{C,t}, r_t, Q_{U,t}, Q_{C,t}, \bar{Q}_{U,t}, \bar{Q}_{C,t}, P_{U,t}, P_{C,t}, w_t)$ such that all agents' problems are optimized, and the markets for labor, capital goods, intermediate goods, final goods, and loans all clear.

## 6.3 Calibration

We calibrate the model at quarterly frequency. The full set of parameters can be found in Table 6.1.

**Preferences.** The entrepreneurs' discount factors $\beta_U, \beta_C$ are set to 0.99, following Jermann (1998), who finds that this value generates a realistic payout yield. For the curvature of utility, we set $\psi_U = \psi_C = 0.01$, implying an elasticity of intertemporal substitution (EIS) of 100. The purpose of this curvature in the model is to encourage firms to smooth dividends, so this very high EIS represents a weak but nonzero motivation to smooth

[60] The difference between $Q_{j,t}$ and $\bar{Q}_{j,t}$ is second order and disappears in the linearized solution.

Table 6.1: Parameter Values: Baseline Calibration (Quarterly)

| Parameter | Name | Value | Internal | Target/Source |
|---|---|---|---|---|
| | | *Preferences* | | |
| Entrepreneur Discount Factor (U) | $\beta_U$ | 0.99 | N | Jermann (1998) |
| Entrepreneur Discount Factor (C) | $\beta_C$ | 0.99 | N | Jermann (1998) |
| Entrepreneur Utility (U) | $\psi_U$ | 0.01 | N | See text |
| Entrepreneur Utility (C) | $\psi_C$ | 0.01 | N | See text |
| Saver Utility (S) | $\psi_S$ | 0 | N | Risk neutral |
| Saver Discount Factor | $\beta_S$ | 0.99 | N | See text |
| Saver Labor Disutility | $\varphi$ | 0.5 | N | Standard |
| Saver Labor Disutility | $\chi$ | 0.542 | Y | $N = 1$ |
| Holding Cost | $\zeta_L$ | 25 | N | See text |
| Holding Cost | $\eta$ | 0.625% | Y | 250bp Spread (Ann.) |
| Credit Line Spread | $\bar{s}_U$ | 0.625% | N | 250bp Spread (Ann.) |
| | | *Government* | | |
| Corporate Tax Rate | $\tau$ | 0.35 | N | Standard |
| Inflation Rate | $\bar{\pi}$ | 1.005 | N | 2% inflation |
| | | *Financial* | | |
| Minimum Payout | $1 - \gamma_C$ | 0.02 | N | See text |
| Minimum Payout | $1 - \gamma_U$ | 0.000 | N | See text |
| Debt-to-EBITDA Limit | $\theta$ | 15 | N | Dealscan |
| Covenant Smoothing | $\rho_L$ | 0.75 | N | 4Q smoothing |
| Covenant Fee | $\kappa$ | 0.010 | N | See text |
| Idio. EBITDA Vol. | $\sigma_\omega$ | 0.400 | N | See text |
| | | *Technology* | | |
| Capital Share | $\alpha$ | 0.33 | N | Standard |
| Capital Adjustment Cost | $\zeta_K$ | 0.5 | N | Standard |
| Variety Elasticity | $\epsilon_y$ | 2.000 | N | See text |
| Labor Sector Elasticity | $\epsilon_n$ | 2.000 | N | See text |
| Unconstrained Share | $a_U$ | 0.326 | N | Asset shares |
| Productivity | $\log \bar{Z}$ | -0.626 | Y | $Y = 1$ |
| Productivity | $\rho_Z$ | 0.75 | N | SPF Forecast |

dividends, and is consistent with corporate payouts being much more volatile than consumption in the data.

Turning to the saver, we set the discount factor $\beta_S$ to 0.99, implying symmetry with the entrepreneur, and a steady-state annualized real interest rate of 4 percent. Saver labor disutility is calibrated so that $\varphi$, the inverse Frisch elasticity, is equal to 0.5, while the multiplicative term $\chi$ is set so that $N = 1$ in steady state. For simplicity, we set $\psi_S = 0$, so that the saver is risk neutral, which implies a constant real rate and also eliminates wealth effects on labor supply. For the holding cost, we assume an elasticity ($\zeta_L$) of 25, implying that a 4 percent increase in the stock of debt should double spreads. While this may be an exaggeration in the long run, we consider this calibration reasonable for capturing short-run reactions to credit flows. The coefficient $\eta$ is set to ensure a steady-state spread of 250 basis points, while $\bar{s}_U$ is chosen to ensure the same spread on credit lines.

**Government.** For the government sector, we choose a steady-state inflation rate of 2 percent annually, and a corporate tax rate of 35 percent.

**Financial.** For the financial variables, we set the exit rate for unconstrained firms to zero, and set the exit rate for constrained firms to 2 percent, close to the value used in Bernanke, Gertler and Gilchrist (1999). For the debt covenants, we choose a debt-to-EBITDA limit of 3.75 (annual), in line with the evidence in Greenwald (2019). We set the smoothing parameter $\rho_L$ to 0.75, consistent with covenants typically measuring EBITDA over the previous four quarters. We parameterize the $\omega_{i,t}$ distribution as a 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 $\kappa_U, \kappa_C$ and the idiosyncratic volatilities $\sigma_{\omega,U}$ and $\sigma_{\omega,C}$ so that each sector of firm has leverage 0.3, and each sector violates its covenants with probability 0.25. Our leverage target is motivated by typical leverage ratios in our data, while the violation target matches the rate found in Chodorow-Reich and Falato (2020). Using alternative values for these parameters had little influence on the results provided they yield reasonable values for firm leverage.

**Technology.** We set the capital share to $\alpha = 0.33$, a standard value. 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 $\zeta_K = 0.5$, which is in the typical range used by the literature and generates a reasonable investment response to a TFP decline. For the other coefficients, we set

$$\phi_0 = \delta\left(\frac{\zeta_K}{\zeta_K - 1}\right), \qquad \phi_1 = \delta^{\zeta_K}$$

to ensure that $\Phi(i) = i$ and $\Phi'(i) = 1$ in steady state.

For the final goods aggregator, we choose $\epsilon_y = 2$, implying a lower elasticity between these sectors than typically used between monopolistically competitive goods. We symmetrically set $\epsilon_n = 2$. We choose the weights $a_U = 0.326$ and $a_C = 1 - a_U$, so that unconstrained firms hold 50 percent of assets in equilibrium. This is consistent with the shares of output produced by public and private firms, respectively, in our data, which could therefore be interpreted as unconstrained and constrained firms. This division is also consistent with Bernanke and Gertler (1995), who find groupings among firms with more and less access to credit in these proportions, and Bernanke, Gertler and Gilchrist (1999), who calibrate their heterogeneous types extension to these ratios. Experiments allowing the unconstrained firms to hold a relatively larger share of assets yielded qualitatively similar results.

For productivity, we set the average level $\bar{Z}$ so that steady-state output is normalized to unity, and the persistence $\phi_Z = 0.75$ to match the COVID-19 output scenario implied by the Survey of Professional Forecasters.[61]

## 6.4 Results

We study the response of the economy to an adverse TFP shock, designed to mimic the COVID-19 episode. Specifically, we consider linearized impulse responses to the shock $\varepsilon_Z = -0.0552$, a magnitude that is chosen to match the decline in GDP in 2020:Q2 in our benchmark ("Credit Lines") specification.[62]

**Unconstrained vs. Constrained Response.** To build intuition, we first show how the responses of constrained and unconstrained firms would differ in the absence of credit lines. To this end, Figure 6.1 compares impulse responses from the baseline model with both types of firms, but terms loans only ("Term Loans"), to an economy with only unconstrained firms and term loans ("All Unconstrained") and an economy with only constrained firms and term loans ("All Constrained"). Specifically, for the All Unconstrained economy, we set the exit rate $1 - \gamma_C = 1 - \gamma_U = 0$, so that (6.9) is slack for both sectors, while for the All Constrained economy, we set the exit rate $1 - \gamma_C = 1 - \gamma_U = 0.02$, so that (6.8) binds for both sectors. To abstract from credit lines, we assume that the firms in the unconstrained firm economy also use term loans, so that the unconstrained spread

[61] This forecast projected 2020:Q2 output growth of -32.2 percent and 2020:Q3 output growth of 10.6 percent, both annualized. The implied quarterly log growth rates are -0.0972 and 0.0252, respectively. Under an AR(1) process beginning from steady state, these rates should correspond to $\varepsilon_{Z,t}$ and $-(1 - \phi_Z)\varepsilon_{Z,t}$, respectively. Solving for two equations in two unknowns yields $\phi_Z = 0.741$. Forecast source: https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/2020/survq220.

[62] This decline in productivity is smaller than the 9.5% target drop in GDP due to the endogenous reduction in labor hours, which amplifies the impact of the shock on output.

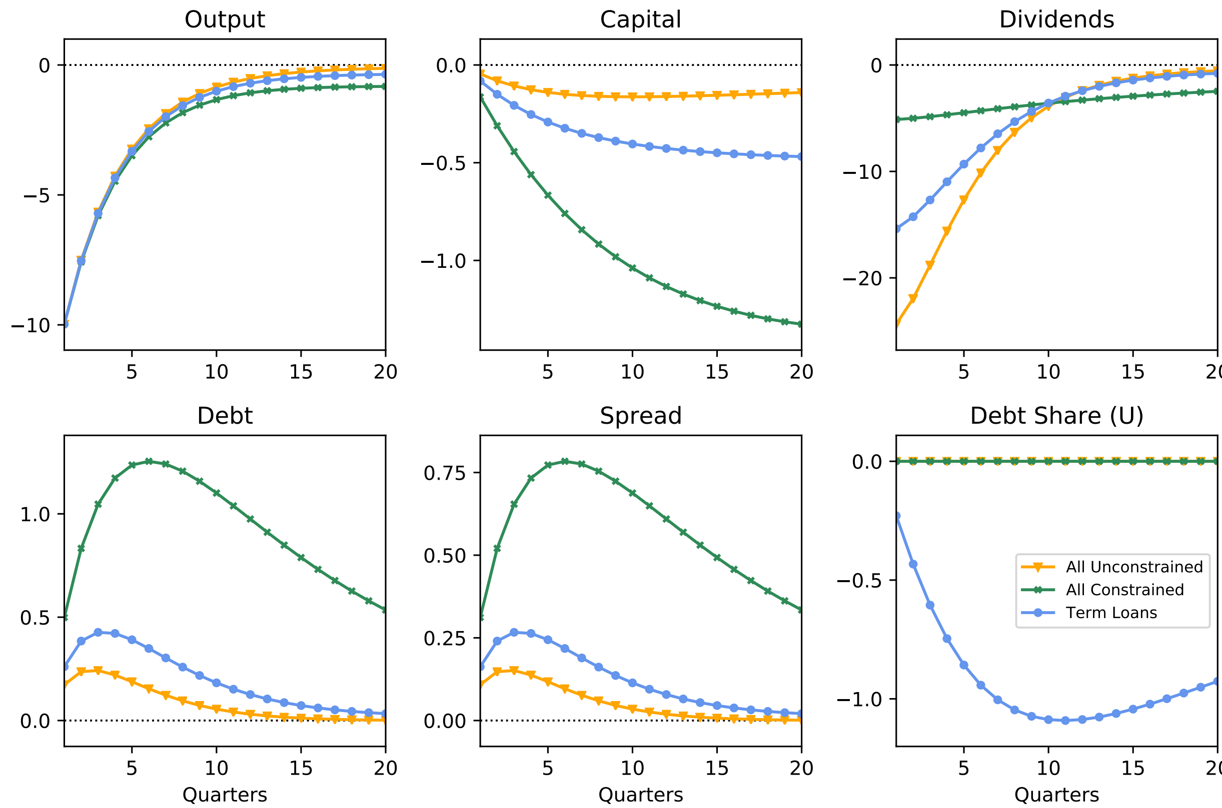


Figure 6.1: Aggregate Responses, Constrained vs. Unconstrained Economies

**Notes:** This figure plots the impulse response to the shock $\varepsilon_Z = -0.0552$. Variable definitions are as follows: "Output" is $Y_t$; "Capital" is $a_U K_{U,t} + a_C K_{C,t}$; "Dividends" is $a_U D_{U,t} + a_C D_{C,t}$; "Debt" is $a_U L_{U,t} + a_C L_{C,t}$; "Spread" is $s_{C,t}$, equivalently $s_{U,t}$ in the All Unconstrained and Term Loans economies; "Debt Share (U)" is $a_U L_{U,t} / (a_U L_{U,t} + a_C L_{C,t})$. All variables except for "Spread" and "Debt Share (U)" are in logs, and all variables are displayed in percent.

$s_{U,t}$ is pinned down by the additional lender optimality condition

$$(1 + r_{U,t}) = (1 + r_t)(1 + s_{U,t}), \qquad s_{U,t} \equiv \eta \left( \frac{L_{U,t} + L_{C,t}}{L_U + L_C} \right)^{\zeta_L}$$

where $s_{U,t}$ is the markup or spread on unconstrained firm debt.

Figure 6.1 shows that a negative productivity shock reduces output in all three economies — mostly due to the loss of productivity, but also partially due to a reduction in factor inputs. This adverse environment also sees investment and dividends fall, while firms increase borrowing in an effort to smooth over this transitory shock. At the same time, the magnitudes of these changes differ across the economies. Notably, investment falls by much more in the All Constrained economy, leading to a 20-quarter decline in the capital stock of 1.33 percent, nearly ten times larger than the 0.14 percent decline observed in the All Unconstrained economy.

To understand this disparity, note that each firm has three potential margins to adjust in response to this adverse shock: it can cut dividends, cut investment, or increase debt. The unconstrained firm has a flexible dividend margin and a weak dividend smoothing motive. This makes reducing dividends relatively favorable compared to decreasing investment, subject to adjustment frictions, or increasing debt, incurring higher expected violation costs.[63] As a result, firms in the All Unconstrained economy cut dividends by 24% on impact, while decreasing investment and increasing debt only modestly.

Constrained firms, on the other hand, already face a binding minimum payout constraint and cannot freely reduce dividends in response to this shock. Although dividends fall slightly due to lower net worth among exiting firms, the binding payout constraint on surviving firms ensures that dividends fall by much less than in the All Unconstrained economy. Instead, firms in the All Constrained economy must utilize their non-dividend margins more intensively, leading to a larger drop in investment, as well as a larger and more persistent increase in debt.

The Term Loans economy, featuring both types of firms, unsurprisingly shows aggregate responses between those of the All Unconstrained and All Constrained economies. Beneath these aggregates, however, lie interesting distributional patterns that emerge as the two types of firms interact in the same economy. To see this, Figure 6.2 shows impulse responses by firm type. The left panels of Figure 6.2 show a sizable flow of credit from unconstrained firms, who now cut borrowing substantially, toward constrained firms, who now increase their debt by roughly twice as much as in the All Constrained economy. As a result, the bottom right panel of Figure 6.2 shows that the share of total debt held by unconstrained firms decreases by 0.93 percentage points over the 20 quarters following the shock.

Since credit flows from firms with a low marginal propensity to invest to firms with a high one, this flow increases aggregate investment in the economy, leading the path for capital and investment in the Term Loans economy to be much closer to their All Unconstrained rather than All Constrained counterparts, despite each type of firm initially holding half the economy's capital. As a result, credit flows in the Term Loans model are able to alleviate some of the excessively large decrease in investment caused by financial constraints.

The intuition behind this flow of credit from unconstrained to constrained firms is simple and likely robust to many alternative model and calibration choices. Because unconstrained firms have a flexible dividend margin that can substitute for adjustments in credit, their demand for credit is more price elastic than that of constrained firms. When spreads rise, unconstrained credit demand therefore drops by relatively more, leading to a relative flow of credit to constrained firms.

[63] Technically speaking, the firm does not directly face investment frictions, but instead enjoys favorable investment pricing through a lower $Q_{j,t}$, due to the investment frictions faced by capital producers.

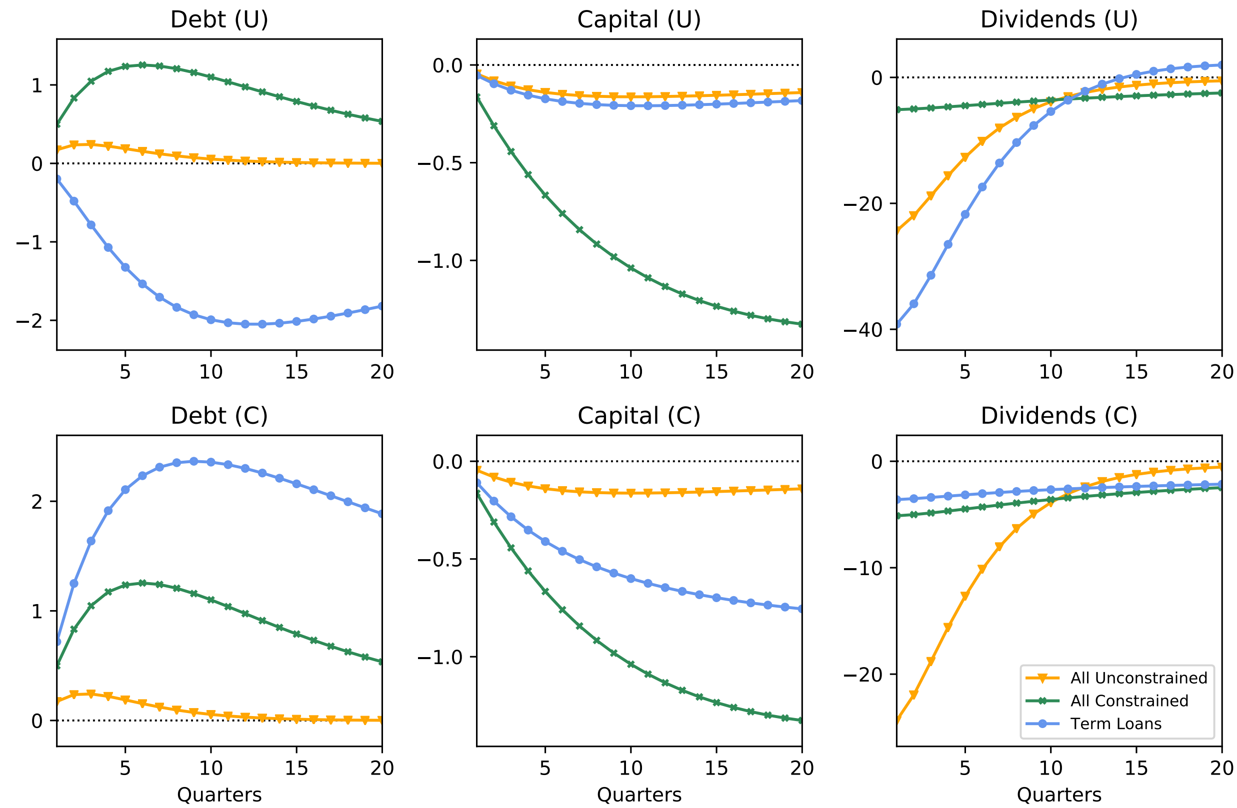


Figure 6.2: Responses by Type, Constrained vs. Unconstrained Economies

**Notes:** This figure plots the impulse response to the productivity shock $\varepsilon_Z = -0.0552$. Variable definitions are as follows: "Debt (U)" is $L_{U,t}$; "Capital (U)" is $K_{U,t}$; "Dividends (U)" is $D_{U,t}$; "Debt (C)" is $L_{C,t}$; "Capital (C)" is $K_{C,t}$; "Dividends (C)" is $D_{C,t}$. All variables are in logs and are displayed in percent. Note that the sector labeled $C$ in the All Unconstrained economy is unconstrained at equilibrium, while the sector labeled $U$ in the All Constrained economy is constrained at equilibrium. Note that these assumptions imply that the type $C$ and type $U$ firms are identical to each other in both the All Unconstrained and All Constrained economies, despite the distinct labels.

Connecting back to the data, however, this pattern contrasts unfavorably with our empirical results, which instead show that the *least* constrained firms dominate the credit response to adverse shocks. Taken together, these findings lead us to conclude that a standard financial frictions model with term lending only is unlikely to match the patterns observed in the data.

**Credit Lines vs. Term Loans.** Starting from this baseline, we now introduce our key institutional feature: credit lines. Specifically, we compare the Term Loans economy described above with a Credit Lines economy in which unconstrained firms borrow at a fixed spread $\bar{s}_U$.[64] Figure 6.3 reproduces the aggregate series shown above, while Figure

[64]Although unconstrained firms have substantial sources of debt finance other than credit lines, for example corporate bonds, this specification can be interpreted as implying that following an adverse shock, these firms leave their non-bank stocks of debt unchanged, while exclusively using their credit lines for

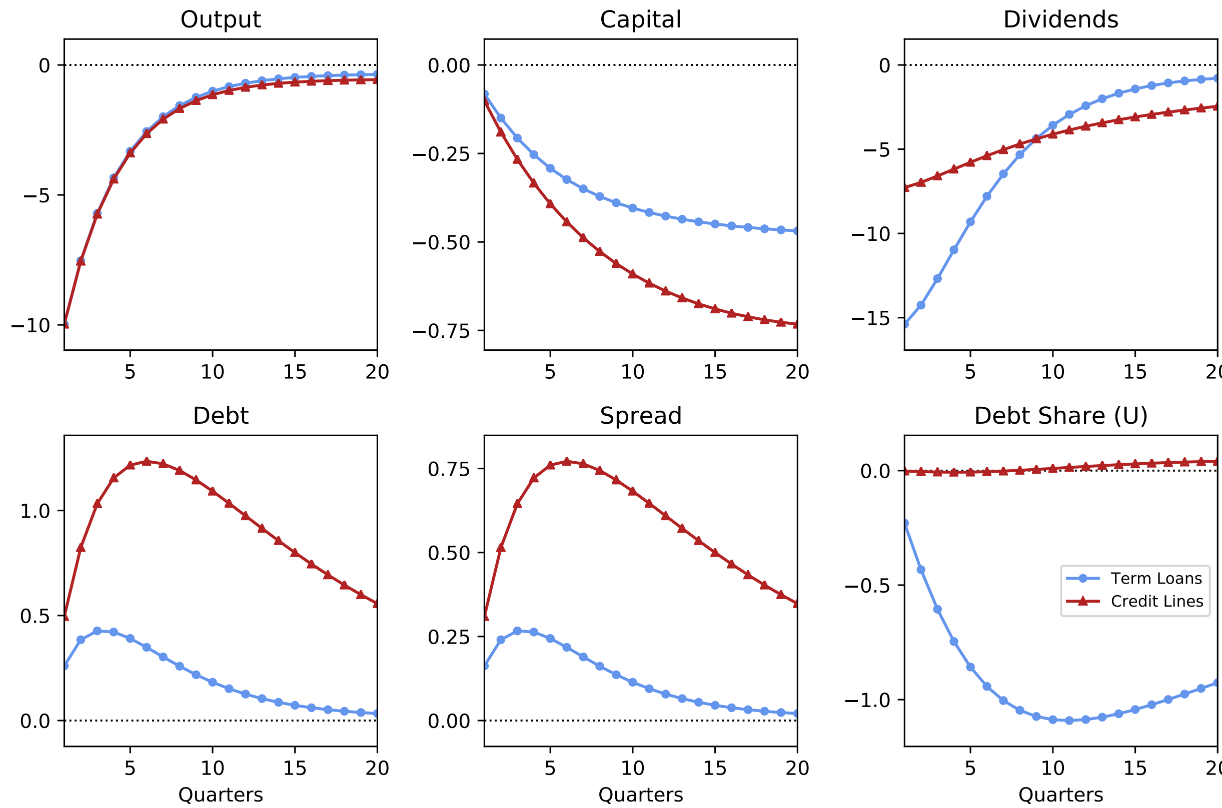


Figure 6.3: Aggregate Responses, Constrained vs. Unconstrained Economies

**Notes:** This figure plots the impulse response to the productivity shock $\varepsilon_Z = -0.0552$. Variable definitions are as follows: "Output" is $Y_t$; "Capital" is $a_U K_{U,t} + a_C K_{C,t}$; "Dividends" is $a_U D_{U,t} + a_C D_{C,t}$; "Debt" is $a_U L_{U,t} + a_C L_{C,t}$; "Spread" is $s_{C,t}$, equivalently $s_{U,t}$ in the Term Loans economy; "Debt Share (U)" is $a_U L_{U,t} / (a_U L_{U,t} + a_C L_{C,t})$. All variables except for "Spread" and "Debt Share (U)" are in logs, and all variables are displayed in percent.

6.4 presents the sector-level results.

Beginning with the sector-level series, Figure 6.4 shows that introducing credit lines reverses the distributional patterns observed in the Term Loan economy. As in our empirical results, the rise in credit is now dominated by unconstrained firms, who increase their borrowing dramatically compared to the Term Loans economy, while constrained firm borrowing is significantly depressed compared to the Term Loans economy. As a result, the relative flow of credit is flipped, with the share of credit held by unconstrained firms now slightly increasing by 0.04 percentage points at the 20-quarter horizon.

This reversal is driven by a change in borrowing incentives for the unconstrained firms. While unconstrained firm credit demand is still as price elastic as it was in the Term Loans economy, the structure of credit lines insulates these firms from rising spreads. Effectively facing below-market interest rates, unconstrained firm credit now expands strongly following the shock. These large credit line draws increase saver holding costs,

credit growth at the margin, consistent with our empirical results.

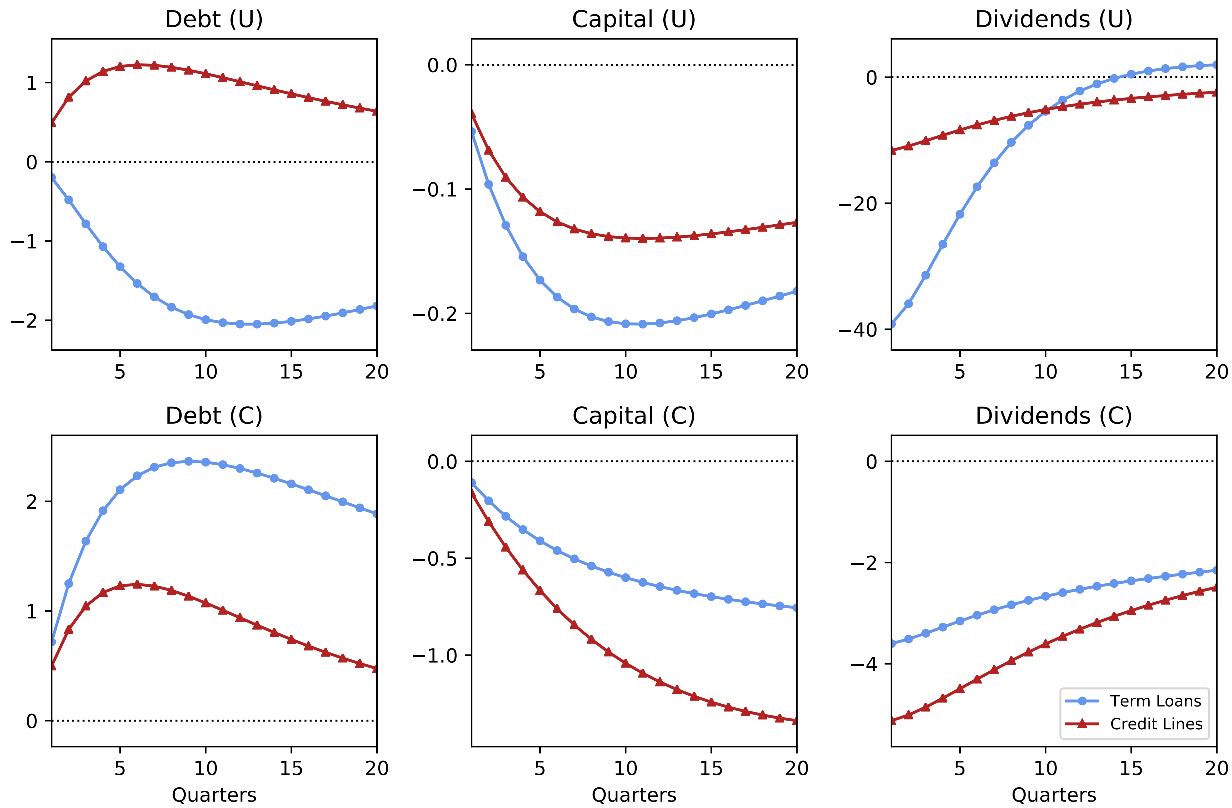


Figure 6.4: Responses by Type, Constrained vs. Unconstrained Economies

**Notes:** This figure plots the impulse response to the productivity shock $\varepsilon_Z = -0.0552$. Variable definitions are as follows: "Debt (U)" is $L_{U,t}$; "Capital (U)" is $K_{U,t}$; "Dividends (U)" is $D_{U,t}$; "Debt (C)" is $L_{C,t}$; "Capital (C)" is $K_{C,t}$; "Dividends (C)" is $D_{C,t}$. All variables are in logs and are displayed in percent.

increasing spreads on term loans, and crowding out borrowing by constrained firms, consistent with our empirical findings in Section 5.2.

Turning to investment, credit lines introduce two novel and opposing forces. First, credit lines lead to an *aggregate effect* on investment by increasing total credit growth in the economy. Although constrained firm borrowing is depressed under credit lines due to crowding out, constrained firm credit demand is more inelastic than that of unconstrained firms. As a result, constrained firm credit does not fall by as much as unconstrained firm credit rises, leading to a net expansion of credit — a substantial increase that is consistent with the aggregate credit responses documented in our empirical work. Indeed, Figure 6.3 shows that aggregate debt rises by several times more in the Credit Lines economy relative to the Term Loans economy. Because both types of firm have a positive marginal propensity to invest out of new debt, this effect causes an increase in investment. At the same time, credit lines introduce a *distributional effect* by reallocating credit across the firm distribution. Since unconstrained firms have a lower marginal propensity to invest, shifting relatively more credit toward these firms leads to a reduction in investment.

Whether the aggregate or distributional component of the credit line channel dominates is a quantitative question that may depend on the specifics of the model and its calibration. Figure 6.3 shows that under our specification the distributional effect dominates, leading to a larger 20-quarter drop in capital in the Credit Lines economy (0.73 percent) relative to the Term Loans economy (0.47 percent). To interpret these magnitudes, we can compare these responses to those of the All Unconstrained, in which the model's main financial friction — the minimum payout constraint — is absent. This corresponding decline in capital in the All Unconstrained economy is 0.14 percent, implying that the introduction of credit lines worsens the excess decline in capital due to payout constraints by 80 percent. The large rise in aggregate debt under term loans, instead flows mostly toward increased payouts for unconstrained firms, leading to a 52 percent smaller fall in aggregate dividends on impact in the Credit Lines economy relative to the Term Loans economy.

To break out the strength of the distributional effect, we can consider a counterfactual economy in which the *constrained* firms, rather than the unconstrained firms, have access to the credit line technology. Under this economy, shown in Appendix Figure F.1 and F.2, the aggregate and distributional effects now push in the same direction, since aggregate credit not only increases, but flows to constrained firms with the highest marginal propensity to invest. Under this economy, the 20-quarter decline in capital is only 0.68 percent, now *reducing* the distortion relative to the All Unconstrained economy by 15 percent. These results imply a quantitatively strong distributional effect of credit lines.

**Discussion and Future Work.** These patterns provide important context for our empirical findings. While our empirics show that large, unconstrained firms dominate the credit response to adverse shocks via draws on their credit lines, they do not speak to how much credit each type of firm would have obtained in the absence of credit lines. In particular, one might imagine that credit lines provide a convenient way for large firms to expand credit at these times, but that they would have readily substituted a similar amount term loans, leading to similar economic outcomes. Our theoretical results weigh against this hypothesis, showing that credit lines are not simply one among many interchangeable credit instruments, but instead fundamentally change the relative flow of credit across the firm distribution.

We view our empirical and theoretical analysis as a partial step towards developing realistic frameworks that focus on the flows and reallocation of credit across firms and other agents. We perceive many avenues for extensions and improvements, of which we highlight three. First, we note that our model's direct implications for output are small. This is unsurprising given that our model features no nominal rigidities, and few frictions on the labor market. As a result, the only distortions that can occur are through the capital stock, which is a highly inertial variable, and experiences a small proportional decline during a recession of limited duration. We suspect that many of the additional mechanisms developed to explain the declines in productivity and labor demand following the 2008 financial crisis, such as working capital constraints, may also amplify the output effects of the credit line channel.

Second, while our analysis primarily focuses on bank-firm lending. However, non-bank lending to firms and households has become increasingly important over the last years (Adrian and Shin, 2009; Crouzet, 2020). Extending both our empirical analysis and the model to such additional forms of financing would provide additional realism and uncover potentially novel mechanisms (see, for example, Buchak et al. (2018), and Elliott et al. (2019) for recent efforts in this direction).

Third, for simplicity, we have abstracted away from explicitly modeling financial intermediaries. In the context of credit lines, we thereby also eliminated at least one potentially powerful mechanism. Banks that experience drawdowns on credit lines may largely extend credit at lower margins than they otherwise could at prevailing market rates. Credit line draws can therefore lower net interest margins, potentially reducing bank net worth and further restricting credit supply.

# 7 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 allow for a large expansion of aggregate firm credit following adverse shocks, they also crowd out credit to constrained firms in favor of unconstrained firms, potentially depressing firm investment. Our theoretical results show that the predetermined pricing and terms of credit lines are key to this relative flow of credit, which would otherwise favor constrained firms following adverse shocks to productivity.

Looking ahead, our work has implications for both research and policy. On the research side, workhorse macro models, such as Bernanke, Gertler and Gilchrist (1999) and Kiyotaki and Moore (1997), impose that the corporate sector is financially constrained, and is either unable to borrow further or dissuaded from doing so by rising credit spreads. Our data show instead that, in the aggregate, firms have access to enormous amounts of committed credit under predetermined conditions. These findings imply that the financial accelerator mechanism depends crucially on the allocation of credit across the firm distribution, and not merely on aggregate quantities. We encourage researchers to view the reallocation of credit between firms as of primary importance in developing future models and theories of the credit channel and the financial accelerator.

On the policy side, we show that while the liquidity that banks provide via credit lines may be beneficial to firms, this provision of promised credit can have negative side effects. We find that banks experiencing larger drawdowns on their credit lines during the COVID-19 pandemic decreased term lending by more. This crowding out effect was strongest for credit types that are more prevalent among smaller, more constrained firms and likely extend to other forms of credit, such as consumer loans, which are not part of our analysis. Surprisingly, this relation is found within an environment of plentiful liquidity and remains nearly unchanged when controlling for bank deposit inflows at this time, indicating that the pressures on bank balance sheets is not purely based on bank access to liquidity.

For policymakers, these findings could motivate various policy interventions during severe crises, especially the ones that aim to provide credit to SMEs directly like the "Paycheck Protection Program." The effects that we document may have been even stronger without some of the policy interventions, including certain programs that were not directly targeting credit access for SMEs. For example, the corporate bond market interventions by the Federal Reserve may have eased the pressure on bank balance sheets because large firms drew down less of their credit lines or repaid some of them. In turn, the spillover effect to term lending may have been reduced because of that. At the same time, our results highlight the risks inherent in banks' undrawn credit lines, implying that regulatory treatment of unused credit capacity should be carefully calibrated to account for the macroeconomic externalities demonstrated here.

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# APPENDIX

## A Aggregate Responses to Monetary Policy Shocks

### A.1 Further Evidence and Robustness

In this Appendix, we describe the estimations of the impulse responses in Figure 1.2 and provide further evidence and robustness checks. Based on the identified monetary policy shocks, we run a series of local projections. Let $y_t$ be the outcome variable at time $t$, e.g., (log) real credit or the federal funds rate. Following Jordà (2005), we estimate

$$y_{t+h} - y_{t-1} = \alpha^h + \beta^h \cdot \epsilon_t^{MP} + \boldsymbol{\gamma^h X_{t-1}} + u_t^h \quad , \tag{A.1}$$

where $h = 0, 1, .., 48$. The estimated coefficients $\beta^h$ give the percentage (point) change at horizon $h$ to a 100-basis-point monetary policy shock $\epsilon_t^{MP}$. $X_{t-1}$ denotes a vector of controls. The specification in Figure 1.2 includes one year of lagged values of the monetary policy shock and one year of lagged values of the one-month change in the respective dependent variable.[65] We check and confirm the robustness of the results to the choice of the lag length, as explained below. Figure A.1 replicates the results in Figure 1.2 and additionally shows the responses for "Deposits," "Loans & Leases," and "Securities." Importantly, in response to a monetary policy tightening, deposits flow out of the banking sector (Drechsler, Savov and Schnabl, 2017), in contrast to the behavior of deposits around the outbreak of Covid-19 (see Figure 1.1). This deposit outflow may be an additional source of bank credit supply contraction after a monetary policy tightening.

In Figures A.2-A.4, we provide further evidence for the results in Figure 1.2. First, we estimate the local projections at a quarterly frequency, the corresponding frequency of the Y14 data (see Figure A.2). The results are largely unchanged and additionally show that GDP contracts after a monetary tightening. Second, we test whether the findings depend on the choice of the lag length. Figure A.3 shows that the results remain much the same whether any, one year, or two years worth of controls of the shocks and the one-month change in the dependent variable are added. Third, we check whether the responses depend on the monetary policy identification approach. Using the high-frequency identification approach (see e.g., Gürkaynak, Sack and Swanson, 2005), Figure A.4 shows impulse responses to the shock series from Nakamura and Steinsson (2018) for the sample 1994:M1 - 2007:M12.[66] Apart from the CPI response, which shows a price puzzle initially,

[65] We do not include controls in the equation for the federal funds rate, since the rate responds on impact to the shock. The responses of the federal funds rate are largely unaffected by including additional controls.

[66] The policy news shock series by Nakamura and Steinsson (2018) is the first principal component across

the remaining responses are similar compared with the ones in Figure 1.2.

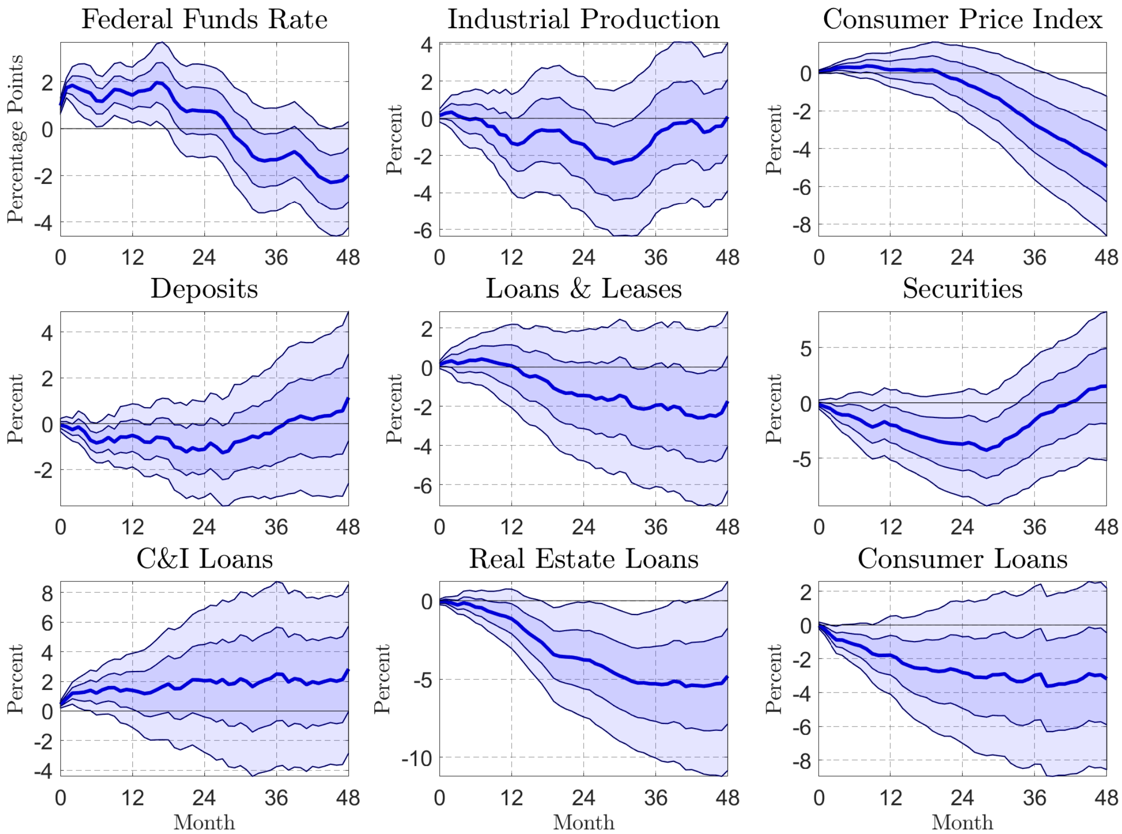


Figure A.1: Impulse Responses to a Monetary Policy Shock.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the identification approach by Romer and Romer (2004). The shock series is taken from Coibion et al. (2017) and the remaining data are obtained from St. Louis Fed's FRED database. The credit series are based on the H.8 releases for U.S. commercial banks from the Board of Governors of the Federal Reserve (see Table B.1 in Appendix B.1 for details about the data). Sample: 1970:M1 - 2007:M12. 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

surprise changes of five futures contracts around scheduled policy announcements: the one with respect to the Fed funds rate immediately following a meeting by the Federal Open Market Committee (FOMC), the expected federal funds rate immediately following the next FOMC meeting, and expected three-month eurodollar interest rates at horizons of two, three, and four quarters. These are the same contracts that are used in the rotations by Gürkaynak, Sack and Swanson (2005). We do not additionally standardize the resulting shock series.

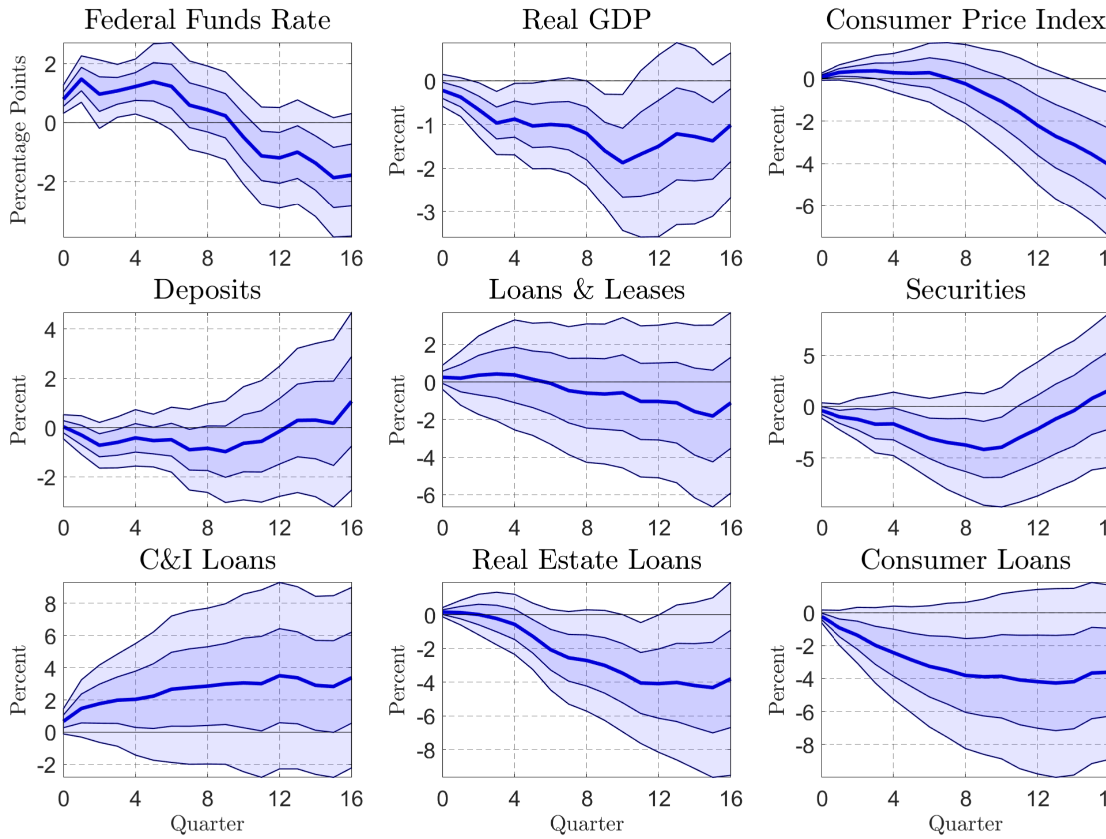


Figure A.2: Impulse Responses to a Monetary Policy Shock – Quarterly Frequency.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the identification approach by Romer and Romer (2004) at a quarterly frequency and the local projection specification in (A.1). The shock series is taken from Coibion et al. (2017) and the remaining data are obtained from St. Louis Fed's FRED database (see Table B.1 in Appendix B.1 for details about the data). Sample: 1970:M1 - 2007:M12, the shocks in 1980:M4 - 1980:M6 and 1980:M9 - 1980:M11 are excluded following Coibion (2012). 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

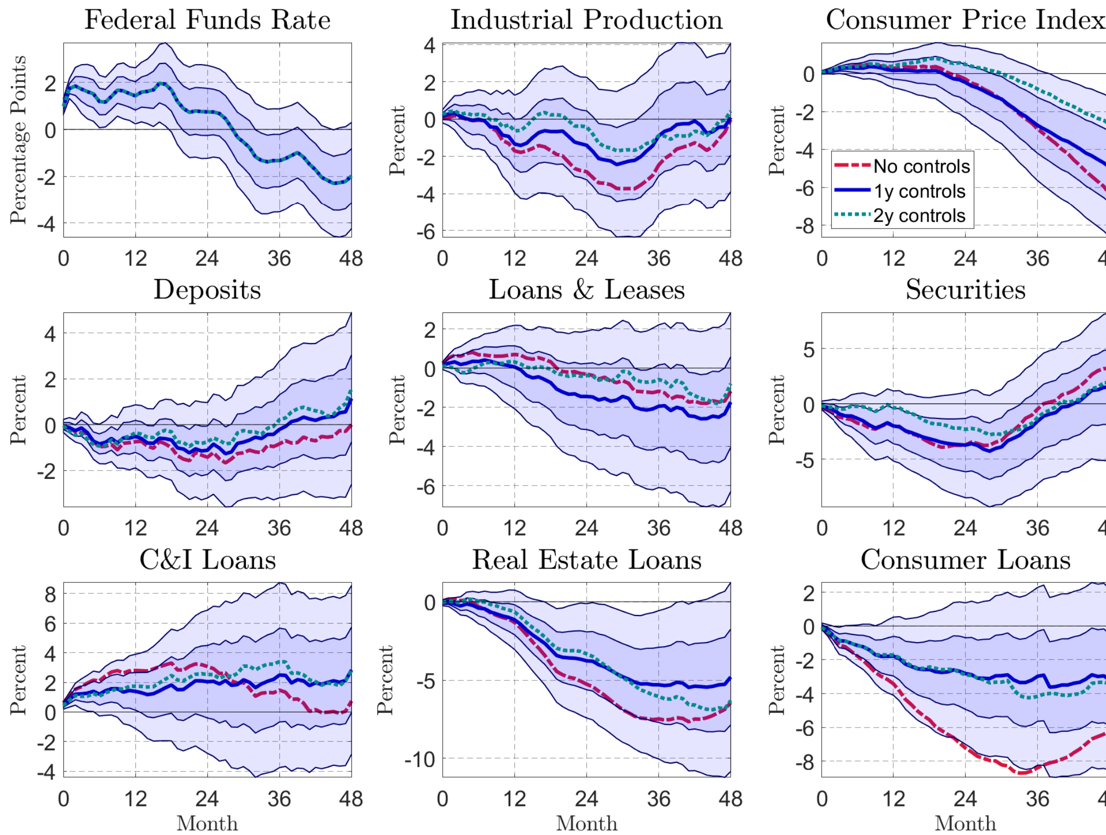


Figure A.3: Impulse Responses to a Monetary Policy Shock – Lag Length.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the identification approach by Romer and Romer (2004) and the local projection specification in (A.1). The estimations differ according to the controls that are included (no controls, one year, or two years). The shock series is taken from Coibion et al. (2017) and the remaining data are obtained from St. Louis Fed's FRED database (see Table B.1 in Appendix B.1 for details about the data). Sample: 1970:M1 - 2007:M12, the shocks in 1980:M4 - 1980:M6 and 1980:M9 - 1980:M11 are excluded following Coibion (2012). 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

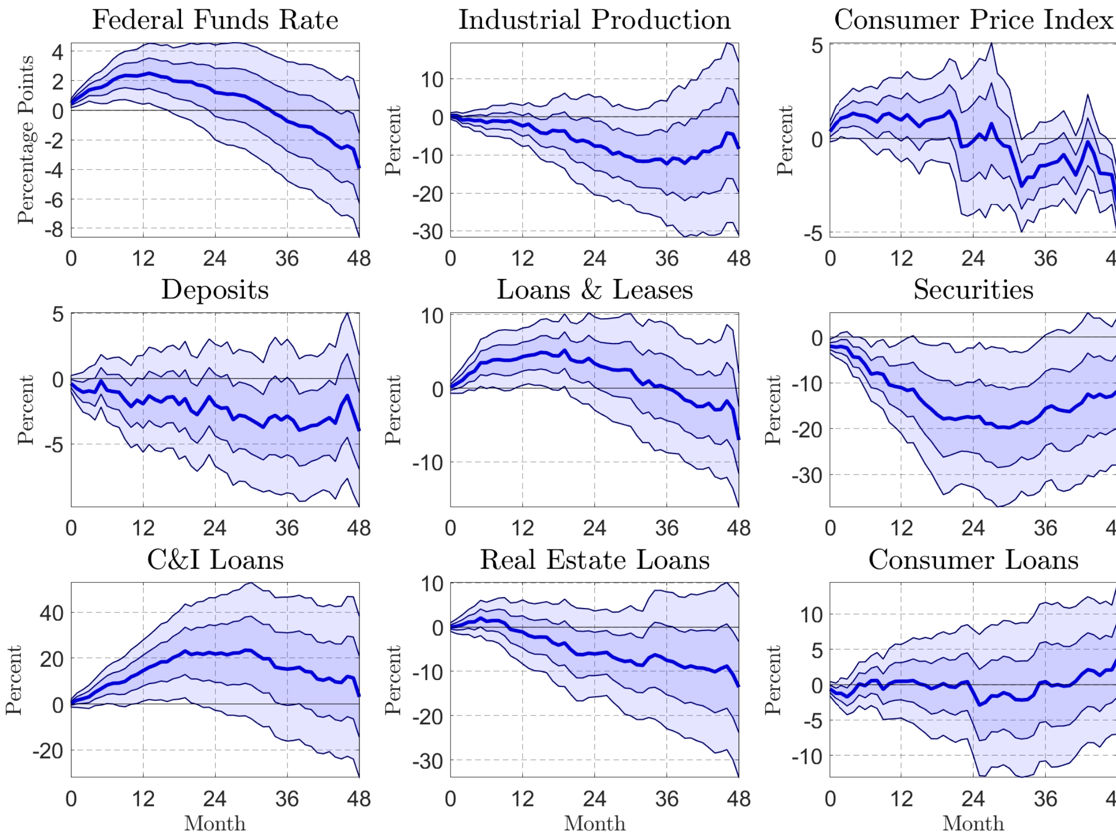


Figure A.4: Impulse Responses to a Monetary Policy Shock − High-Frequency Surprises.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the local projection specification in (A.1). The shock series follows the computations in Nakamura and Steinsson (2018) (see also footnote 66) and the remaining series are obtained from St. Louis Fed's FRED database (see Table B.1 in Appendix B.1 for details about the data). All specifications exclude additional controls, apart from the estimations for industrial production and the consumer price index, for which two years worth of the shocks and the one-month change in the respective dependent variable are included. Sample: 1994:M1 - 2007:M12. 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

## A.2 Commercial Paper and Corporate Bond Spreads

One channel through which a monetary policy tightening may lead to an increase in C&I loans is by decreasing liquidity and raising the cost of funding in commercial paper markets. As shown by Gatev and Strahan (2006), an increase in the commercial paper spread leads to an increase in C&I loans, likely due to the fact that firms draw on their existing credit lines when the relative cost of commercial paper increases. In Figure A.5, we confirm this relation based on the sample 1990:M1 - 2007:M12 (panel c).[67] However, we also show that C&I loans do not generally increase in response to higher spreads. For example, higher corporate bond spreads, measured by changes in the spread by Gilchrist and Zakrajšek (2012) and their excess bond premium series, do not imply such a response of C&I loans, which eventually decrease following a rise in such spreads (panels a and b).[68] One potential reason for these differences is that a monetary policy tightening leads to a persistent increase in the commercial paper spread, whereas the bond spread series do not, as shown in panels (d)-(f) in Figure A.5.

[67] All local projections include one year of lagged values of the monetary policy shock and the one-month change in the respective dependent variable as controls. In unreported results, we find that the responses are similar for a sample that starts in 1973:M1, with the difference that the magnitude of the responses are smaller.

[68] The commercial paper spread series is the difference between the 3-month AA nonfinancial commercial paper rate and the 3-month Treasury bill. Both are taken from St. Louis Fed's FRED database. The series from Gilchrist and Zakrajšek (2012) are available at: https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html

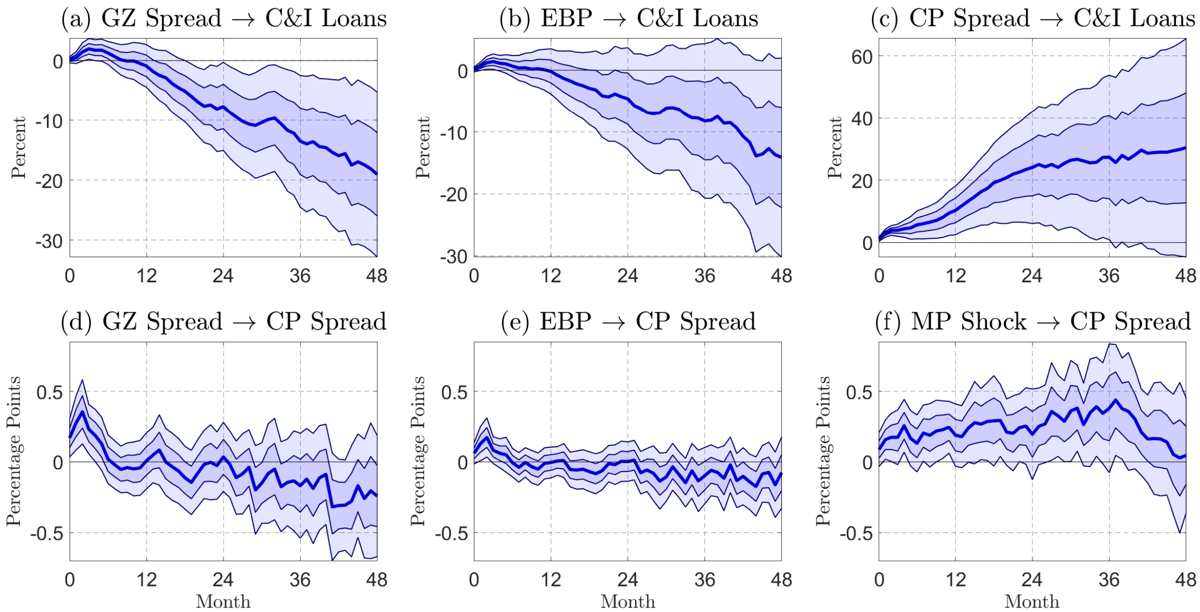


Figure A.5: Impulse Responses of C&I Loans and Commercial Paper Spread.

**Notes:** Estimation results based on the local projection specification in (A.1). Impulse responses to a 1 percentage point increase in the spread series by Gilchrist and Zakrajšek (2012) ("GZ Spread"), their excess bond premium ("EBP"), the commercial paper spread ("CP Spread"), or the Romer and Romer (2004) monetary policy shock series taken from Coibion et al. (2017) ("MP Shock") (see Table B.1 in Appendix B.1 for details about the data). Shock series for the spreads are obtained by computing monthly changes in the respective series. Sample: 1990:M1 - 2007:M12. 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

## A.3 Alternative Sources of Firm Financing

In this Appendix, we document the response of total firm credit to a monetary policy shock. In particular, while credit from banks to firms increases following a monetary policy tightening (Figure 1.2), it may be the case that other types of credit contract, with an ambiguous overall aggregate response. To investigate the response of total firm credit, we use quarterly data from the Flow of Funds (see Table B.1 in Appendix B.1 for details about the data). Figure A.6 shows the impulse responses of various types of credit to nonfinancial businesses following a contractionary monetary policy shock.[69] Nonfinancial businesses can be separated into corporate and noncorporate ones. Nonfinancial noncorporate businesses (e.g., sole proprietorships and limited partnerships) only borrow using loans, and panel (b) shows that such credit contracts to a monetary policy tightening. These loans likely consist of term loans to a large extent and the response is therefore consistent with the results in Section 5.1. In contrast, corporate loans, which include more credit lines, increase as shown in panel (c), again in line with the findings in Section 5.1. In addition, corporate debt securities also rise after an initial dip (see panel d). Commercial paper and corporate bonds, which are both part of corporate debt securities, also increase as shown in panels (e) and (f), after a drop over the first quarters for corporate bonds.[70] Taking all corporate and noncorporate loans and debt securities together, total firm credit also rises following a monetary policy tightening, as shown in panel (a).

[69] All local projections include one year of lagged values of the monetary policy shock and the one-month change in the respective dependent variable as controls.

[70] Related to these findings, Elliott et al. (2019) show that a contractionary monetary policy shock actually shifts credit supply from banks to nonbanks, using data from Dealscan and controlling for firm credit demand using the fixed effects approach by Khwaja and Mian (2008).

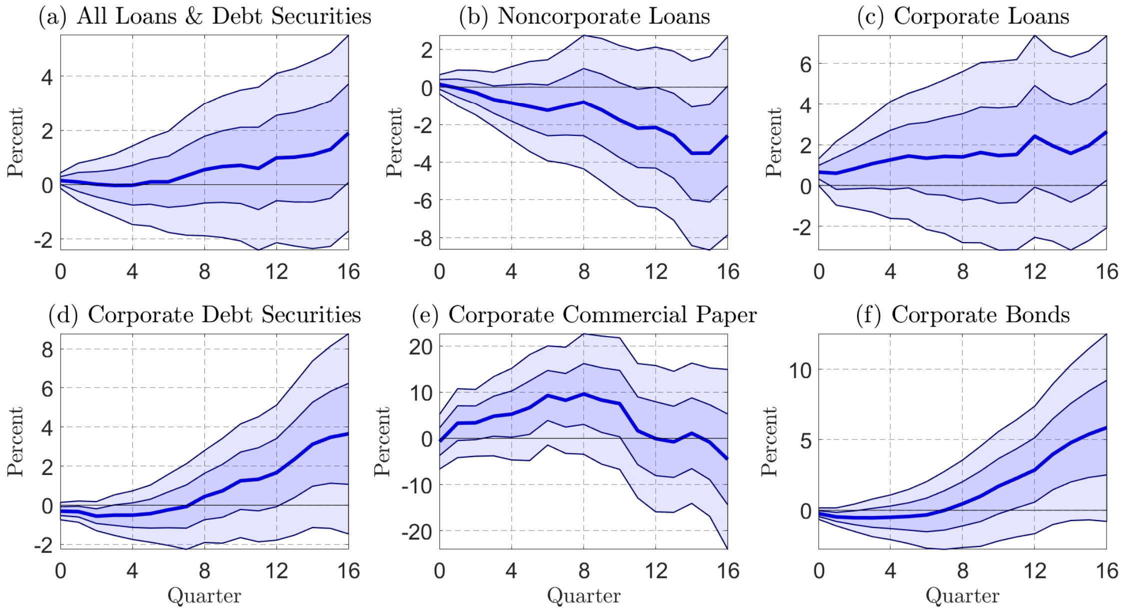


Figure A.6: Impulse Responses to a Monetary Policy Shock − Flow of Funds.

**Notes:** Impulse responses to a 1 percentage point contractionary monetary policy shock based on the identification approach by Romer and Romer (2004) at a quarterly frequency and the local projection specification in (A.1). The shock series is taken from Coibion et al. (2017) and the remaining data are obtained from St. Louis Fed's FRED database (see Table B.1 in Appendix B.1 for details about the data). Sample: 1970:M1 - 2007:M12, the shocks in 1980:M4 - 1980:M6 and 1980:M9 - 1980:M11 are excluded following Coibion (2012). 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors.

# B Data

## B.1 Variable Definitions and Data Sources

In Tables B.1-B.5, we provide names, definitions, and sources for all variables that are used in the empirical analysis. Table B.1 reports the macro time series that are used in Section 1 and Appendix A. 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 used in Sections 3-5 and the Appendix. The variables from the FR Y-9C Filings are described in Table B.5.

Table B.1: Macro Time Series.

| **Variable Name** | **Description** | **Source** |
|---|---|---|
| Bank Credit | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Loans and Leases | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Securities | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| C&I Loans | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Real Estate Loans | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Consumer Loans | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Total Assets | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Deposits | H.8 releases, All U.S. commercial banks, weekly, SA | FRED |
| Federal Funds Rate | Effective funds rate, daily, NSA | FRED |
| Consumer Price Index | All Items for the United States, SA, 2015=100 | FRED |
| Industrial Production | Real Index, 2012=100, SA | FRED |
| Gross Domestic Product | Real, Billions of Chained 2012 Dollars, SA | FRED |
| Gilchrist-Zakrajsek Spread | Based on Gilchrist and Zakrajšek (2012), NSA | FEDS Notes |
| Excess Bond Premium | Based on Gilchrist and Zakrajšek (2012), NSA | FEDS Notes |
| Commercial Paper Spread | Difference between 3-month AA Nonfinancial Commercial Paper Rate (based on discontinued CP Rate until 1997:M8) and 3-month T-Bill | FRED FRED FRED |
| Nonfinancial Business; Debt Securities and Loans | Flow of Funds, NSA | FRED |
| Nonfinancial Noncorporate Business; Loans | Flow of Funds, NSA | FRED |
| Nonfinancial Corporate Business; Loans | Flow of Funds, NSA | FRED |
| Nonfinancial Corporate Business; Debt Securities | Flow of Funds, NSA | FRED |
| Nonfinancial Corporate Business; Commercial Paper | Flow of Funds, NSA | FRED |
| Nonfinancial Corporate Business; Corporate Bonds | Flow of Funds, NSA | FRED |

**Notes:** All nominal credit series are converted into real series using the consumer price index. All weekly or monthly time series are averaged to monthly or quarterly frequency for purposes of computing impulse responses in Figure 1.2 and Appendix A. Notation: "FRED" = St. Louis Fed's FRED Database, "SA" = seasonally-adjusted, "NSA" = non-seasonally-adjusted.

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

| Variable Name | Description | Field No. |
|---|---|---|
| Zip code | Zip code of headquarters | 7 |
| Industry | Derived NAICS 2-Digit 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 | 74 |
| Long Term Debt | Used in calculating implied covenants | 78 |
| Total Liabilities | Total liabilities | 80 |
| Probability of Default | Probability of default for firms subject to advanced approaches for regulatory capital | 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 (see Table B.1). 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 |

**Notes:** All data are obtained from the Wharton Research Data Services. Nominal series are converted into real series using the consumer price index (see Table B.1).

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 (see Table B.1).

Table B.5: 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 |

**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 (see Table B.1). The FR Y-9C form for March 2020 can be found at: https://www.federalreserve.gov/reportforms/forms/FR_Y-9C20200401_f.pdf.

## B.2 Covenants

To account for possible covenant limits, we adjust firms' unused borrowing capacity. 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 $\kappa$ and $\tau$ are relatively stable over time (see, e.g., Figure 2 therein). In particular, weighting loans by the deal-amount, $\kappa$ is around 2.75 and $\tau$ is approximately 3.75. We use these two covenant rules and their approximated values for $\kappa$ and $\tau$ 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.[71] Based on this procedure, we find that around 37 percent of firms violate one of the two constraints in normal times (2012:Q3-2019:Q4). Chodorow-Reich and Falato (2020) find a slightly lower share of violations across loans (around 25 percent). 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.

## B.3 Data Cleaning and Sample Restrictions

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.

[71] 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.

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 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. A loan facility may include both credit lines and term loans. We assume that all unused credit (i.e., committed exposure - utilized exposure) takes the form of unused

capacity on the firm's credit lines. That is, we include unused borrowing capacity on a firm's term loans in the total unused credit line measure.

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

# C Additional Descriptive Evidence

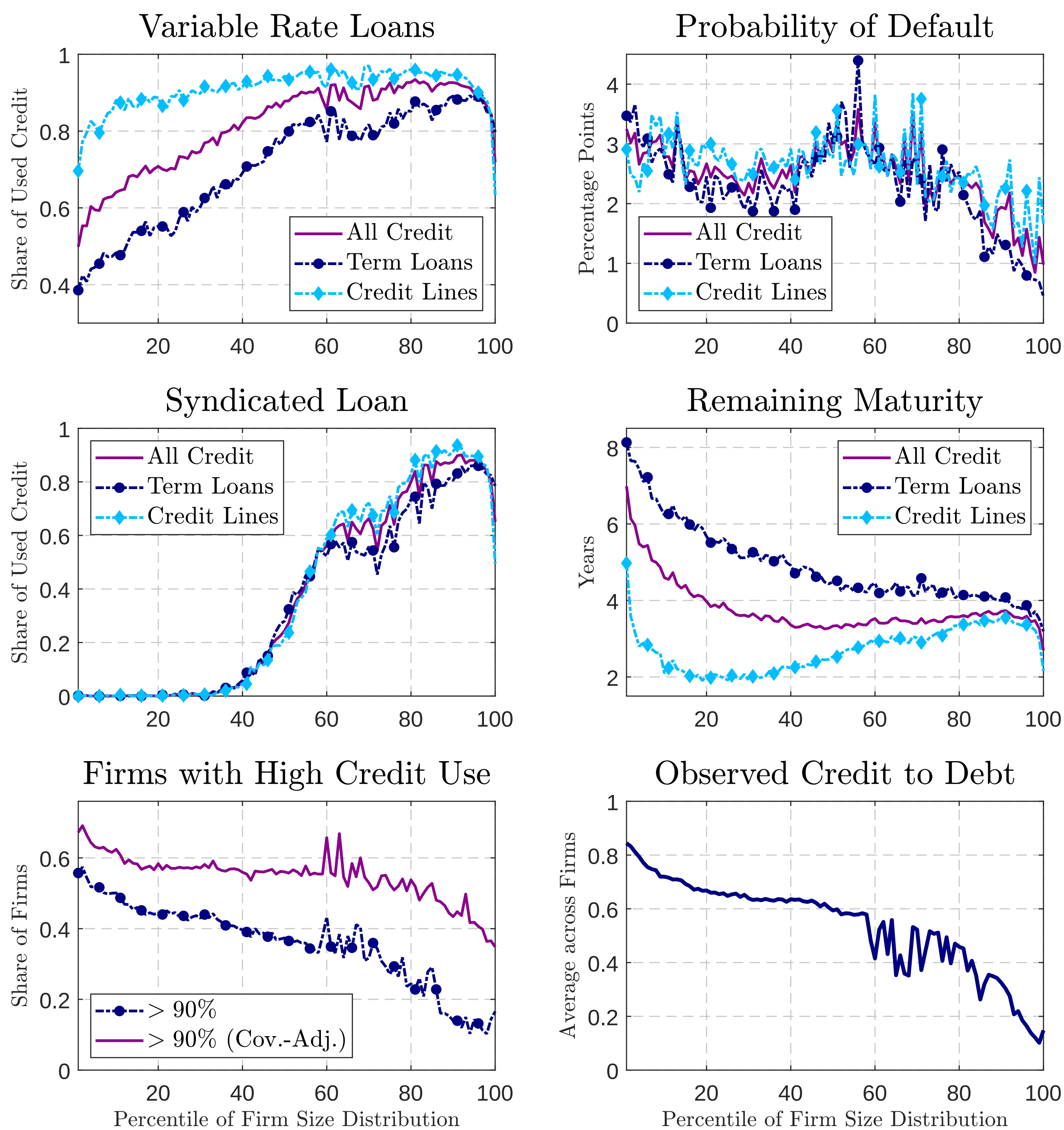


Figure C.1: Credit Characteristics across Firm Size Distribution.

**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 percent of their committed credit, which is additionally adjusted for covenants (see Appendix B.2). The bottom right graph shows the average share of observed credit in our data relative to firm total debt. The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4. See Section 2 and Appendix B for details about the data.

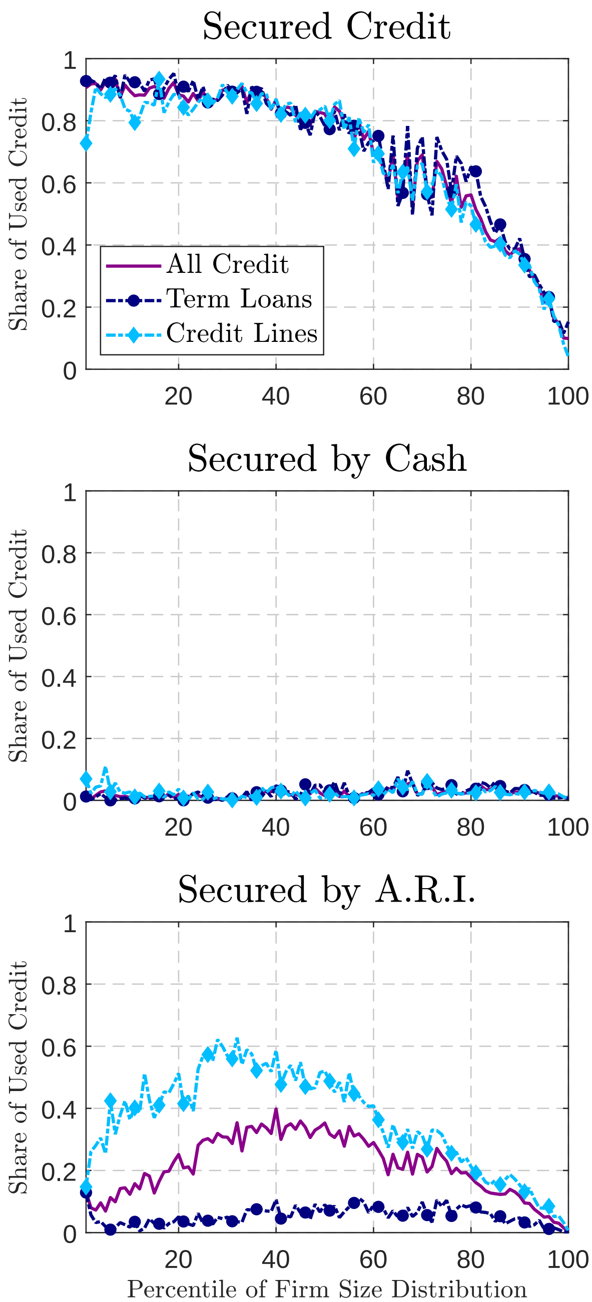


Figure C.2: Credit Characteristics across Firm Size Distribution.

**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. See Section 2 and Appendix B for details about the data.

# D Determinants and Use of Firm Credit

## D.1 Which firms have credit lines and borrowing capacity?

Table D.1: Credit Line Regressions: Covenant Adjustments.

| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
|---|---|---|---|---|---|---|
| | Firm has credit line | | Unused capacity | | Credit intensity | |
| | Commitment | Covenants | Commitment | Covenants | Commitment | Covenants |
| EBITDA | 0.96*** | 1.52*** | 0.13*** | 0.27*** | 0.02*** | 0.25*** |
| | (0.08) | (0.10) | (0.01) | (0.01) | (0.01) | (0.01) |
| Tangible assets | -0.37*** | -0.40*** | 0.13*** | 0.18*** | -0.33*** | -0.28*** |
| | (0.05) | (0.05) | (0.01) | (0.01) | (0.01) | (0.01) |
| Size | 0.16*** | 0.09*** | 0.02*** | 0.02*** | -0.04*** | -0.03*** |
| | (0.01) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| Leverage | -0.95*** | -0.89*** | -0.41*** | -0.58*** | 0.08*** | -0.21*** |
| | (0.07) | (0.07) | (0.01) | (0.01) | (0.01) | (0.01) |
| Investment grade | -0.19*** | -0.12*** | 0.06*** | 0.12*** | -0.05*** | 0.02*** |
| | (0.03) | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) |
| Public firm | 1.67*** | 0.65*** | 0.14*** | 0.14*** | -0.01 | 0.02*** |
| | (0.13) | (0.07) | (0.01) | (0.01) | (0.01) | (0.01) |
| Firm age | 0.10*** | 0.11*** | 0.02*** | 0.02*** | 0.02*** | 0.03*** |
| | (0.02) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) |
| R-squared | 0.14 | 0.10 | 0.21 | 0.27 | 0.21 | 0.12 |
| Observations | 181,780 | 181,780 | 145,547 | 145,547 | 142,368 | 142,368 |
| Number of Firms | 36,883 | 36,883 | 29,820 | 29,820 | 29,450 | 29,450 |

**Notes:** Estimation results for regressions (4.1). "Commitment" refers to the unadjusted committed balances, specifications labeled "Covenants" include adjustments to borrowing capacity to reflect generic covenant restrictions as described in Appendix B.2. Dependent variables are {0,1} variable measuring whether firm has a credit line in columns (i) and (ii), the share of unused borrowing capacity, defined as 1 minus the ratio of used balances to committed balance in columns (iii) and (iv), and a credit line borrowing intensity measure defined as the ratio of unused balances to unused balances plus cash in columns (v) and (vi). The two specifications "Commitment" and "Covenants" are estimated on the same sample for each dependent variable. EBITDA and tangible assets are scaled by noncash assets (total assets minus cash and marketable securities). Size is defined as the natural log of noncash assets. Leverage is the ratio of total liabilities to total assets. Firm age is the natural log of number of periods between the observation date and firm incorporation date, annualized. All regressors are lagged by four quarters. The incidence of a firm having a credit line is estimated as a logit regression, reporting a Pseudo $R^2$. All other specifications are estimated using OLS. Sample: 2012:Q3 - 2019:Q4. All estimations include industry and time fixed effects. Standard errors in parentheses are clustered by firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table D.2: Credit Line Regressions: Private versus Public Firms.

| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
|---|---|---|---|---|---|---|
| | Firm has credit line | | Unused capacity | | Credit intensity | |
| | Private | Public | Private | Public | Private | Public |
| EBITDA | 0.84*** | -0.20 | 0.10*** | 0.04 | 0.02*** | -0.08* |
| | (0.07) | (1.32) | (0.01) | (0.04) | (0.01) | (0.04) |
| Tangible assets | -0.25*** | 0.06 | 0.11*** | 0.13*** | -0.32*** | -0.31*** |
| | (0.04) | (0.36) | (0.01) | (0.01) | (0.01) | (0.02) |
| Size | 0.12*** | 0.43*** | 0.01*** | 0.04*** | -0.04*** | -0.06*** |
| | (0.01) | (0.08) | (0.00) | (0.00) | (0.00) | (0.00) |
| Leverage | -0.97*** | -0.95* | -0.43*** | -0.15*** | 0.09*** | 0.12*** |
| | (0.06) | (0.55) | (0.01) | (0.03) | (0.01) | (0.03) |
| Investment grade | -0.20*** | 0.18 | 0.06*** | 0.05*** | -0.05*** | 0.00 |
| | (0.03) | (0.21) | (0.00) | (0.01) | (0.00) | (0.01) |
| Firm age | 0.10*** | -0.13 | 0.01*** | 0.01 | 0.02*** | 0.04*** |
| | (0.02) | (0.12) | (0.00) | (0.00) | (0.00) | (0.01) |
| R-squared | 0.10 | 0.09 | 0.17 | 0.14 | 0.20 | 0.28 |
| Observations | 216,281 | 28,202 | 177,838 | 27,787 | 131,068 | 27,684 |
| Number of Firms | 42,472 | 1,777 | 35,116 | 1,762 | 29,406 | 1,758 |

**Notes:** Estimation results for regressions (4.1). "Private" and "Public" refer to samples restricted to only private or only public firms, respectively. Committed and unused balances are computed without covenant adjustments. Dependent variables are {0,1} variable measuring whether firm has a credit line in columns (i) and (ii), the share of unused borrowing capacity, defined as 1 minus the ratio of used balances to committed balance in columns (iii) and (iv), and a credit line borrowing intensity measure defined as the ratio of unused balances to unused balances plus cash in columns (v) and (vi). EBITDA and tangible assets are scaled by noncash assets (total assets minus cash and marketable securities). Size is defined as the natural log of noncash assets. Leverage is the ratio of total liabilities to total assets. Firm age is the natural log of number of periods between the observation date and firm incorporation date, annualized. All regressors are lagged by four quarters. The incidence of a firm having a credit line is estimated as a logit regression, reporting a Pseudo $R^2$. All other specifications are estimated using OLS. Sample: 2012:Q3 - 2019:Q4. All estimations include industry and time fixed effects. Standard errors in parentheses are clustered by firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

## D.2 Credit Responses to Cash-Flow Changes

To investigate whether firms with different levels of borrowing capacity prior to a change in cash flow show distinct credit line responses, we extend regressions (4.2) to

$$\frac{L_{i,t+h-3} - L_{i,t-4}}{0.5\,(L_{i,t+h-3} + L_{i,t-4})} = \alpha_i^h + \tau_{t,k}^h + \kappa_m^h + \beta_1^h \frac{\Delta^4 CF_{i,t-4}}{Assets_{i,t-4}} + \beta_2^h \frac{\Delta^4 CF_{i,t-4}}{Assets_{i,t-4}} \cdot Cap_{i,t-4} + \gamma^h \mathbf{X_{i,t-4}} + u_{i,t-3}^h\ , \tag{D.1}$$

where $h = 0, 1, ..., 8$ and $Cap_{i,t-4}$ is the ratio of unused to committed credit of firm $i$ at time $t-4$. Unused credit is the sum of unused credit lines and unused term loans. Figure D.1 shows the negative of the estimated coefficients $\beta_1$ and $\beta_2$. To determine firms' borrowing capacity, we also consider a version that additionally adjusts for covenants as described in Appendix B.2. In addition, we estimate the local projections (4.2) using the committed instead of the used amount of credit for the dependent variable.

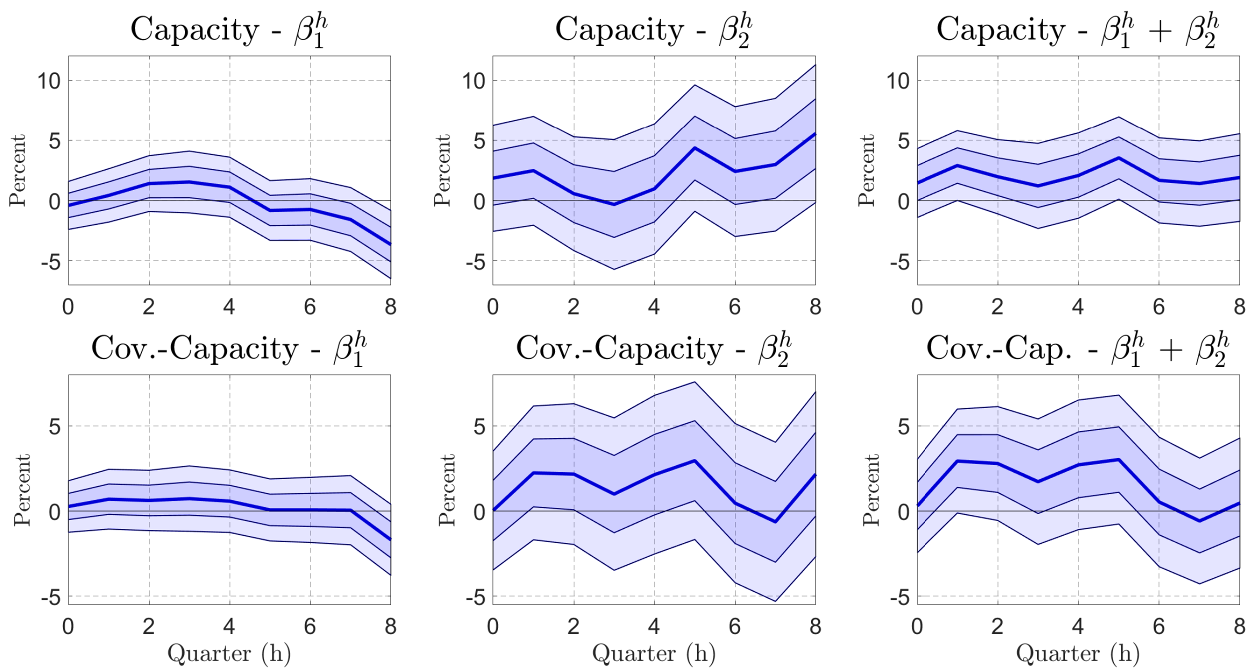


Figure D.1: Credit Responses to a Cash-Flow Change − Borrowing Capacity.

**Notes:** Responses of firms' used credit lines to a one-unit decrease in net income relative to assets, based on the local projection approach in (D.1). The figures at the top show the estimated coefficients for specifications that use firms' lagged borrowing capacity, defined as the ratio of unused credit to committed credit, and the ones at the bottom adjust firms' borrowing capacity for generic covenant limits (see Appendix B.2). The left and the middle graphs give the estimated coefficients $\beta_1^h$ and $\beta_2^h$, and the right figure indicates the sum of the two. Observations with absolute annual changes in net income relative to assets larger than 5 percent are excluded. The estimations are based on a balanced panel of credit lines and term loans with 6,399 observations (top), or 6,357 observations (bottom), respectively, for each impulse response horizon. 95 and 68 percent confidence bands are shown using standard errors that are clustered by firm. Sample: 2012:Q3 - 2019:Q4.

We also consider the specification

$$\frac{L_{i,t+h-3}}{C_{i,t+h-3}} - \frac{L_{i,t-4}}{C_{i,t-4}} = \alpha_i^h + \tau_{t,k}^h + \kappa_m^h + \beta_1^h \frac{\Delta^4 CF_{i,t-4}}{Assets_{i,t-4}} + \gamma^h \boldsymbol{X_{i,t-4}} + u_{i,t-3}^h \ , \tag{D.2}$$

where $h = 0, 1, ..., 8$ and $L_{i,t}/C_{i,t}$ is the ratio of used to committed credit of firm $i$ at time $t$. The estimation results to a negative cash flow change for (D.2) are shown in Figure D.2, again considering a version that additionally adjusts for covenants.

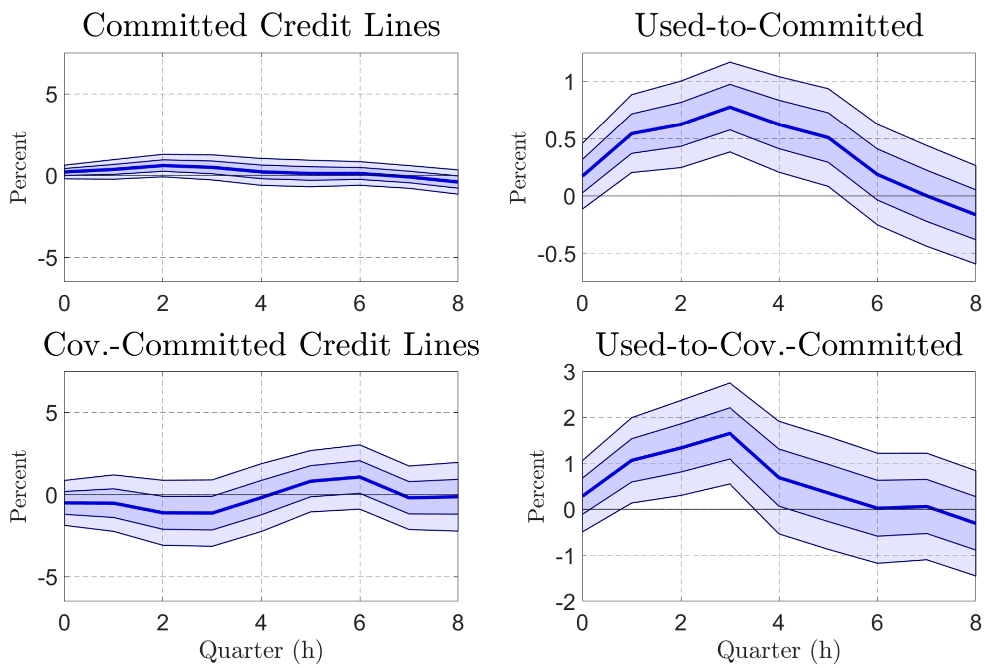


Figure D.2: Credit Responses to a Cash-Flow Change − Committed Credit.

**Notes:** Responses of firms' committed credit lines (left) and the ratio of used-to-committed credit lines (right) to a one-unit decrease in net income relative to assets, based on the local projection approaches in (4.2) and (D.2). Observations with absolute annual changes in net income relative to assets larger than 5 percent are excluded. The estimations are based on a balanced panel of credit lines and term loans with 6,399 observations (top), or 2,224 observations (bottom), respectively, for each impulse response horizon. 95 and 68 percent confidence bands are shown using standard errors that are clustered by firm. Sample: 2012:Q3 - 2019:Q4.

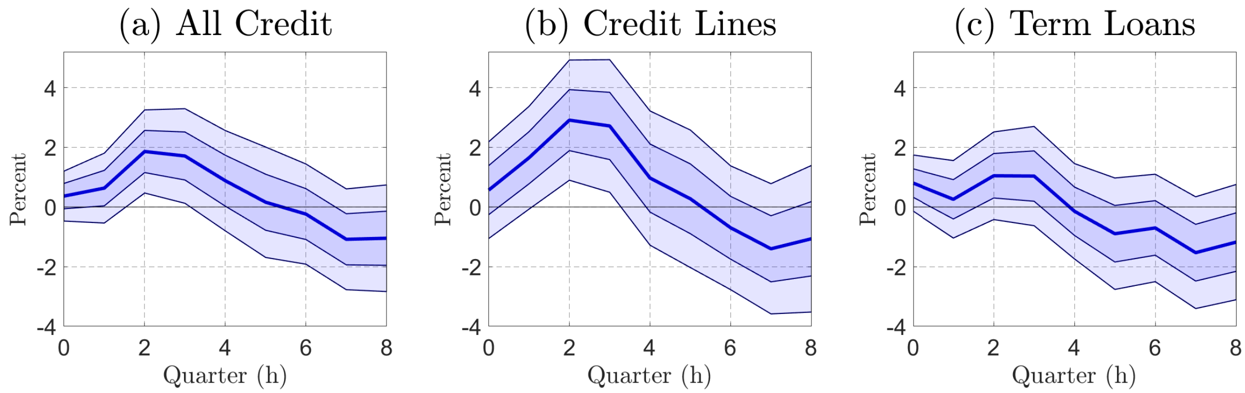


Figure D.3: Credit Responses to a Cash-Flow Change — Robustness: Cash-Flow Change.

**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 (4.2). Observations with absolute annual changes in net income relative to assets larger than 10 percent are excluded. The estimations are based on a balanced panel of credit lines and term loans with 1,674 observations for each impulse response horizon. 95 and 68 percent confidence bands are shown using standard errors that are clustered by firm. Sample: 2012:Q3 - 2019:Q4.

Table D.3: Usage of Credit Lines.

| Credit Facility Purpose | % Committed | % Used |
|---|---|---|
| M&A Financing | 3.5 | 5.7 |
| Capital Expenditures Excluding Real Estate | 1.2 | 2.3 |
| Commercial Paper Back-up | 5.3 | 0.4 |
| Trade Financing | 3.1 | 3.0 |
| Working Capital: Short-Term/Seasonal | 11.8 | 12.7 |
| Working Capital: Permanent | 29.5 | 33.0 |
| General Corporate Purposes | 33.0 | 22.9 |
| Owner-Occupied Commercial Real Estate | 1.2 | 3.5 |
| Dealer Floorplan | 1.5 | 4.1 |
| All Other Categories | 9.9 | 12.5 |

**Notes:** Shares computed based on average credit line commitments and average credit line utilization by category for the sample 2012:Q3 - 2019:Q4. Statistics reported for primary categories of facility purpose as defined in FR Y-14Q data instructions.

# E Behavior of Firm Credit around Macroeconomic Events

## E.1 Credit Responses to Monetary Policy Surprises

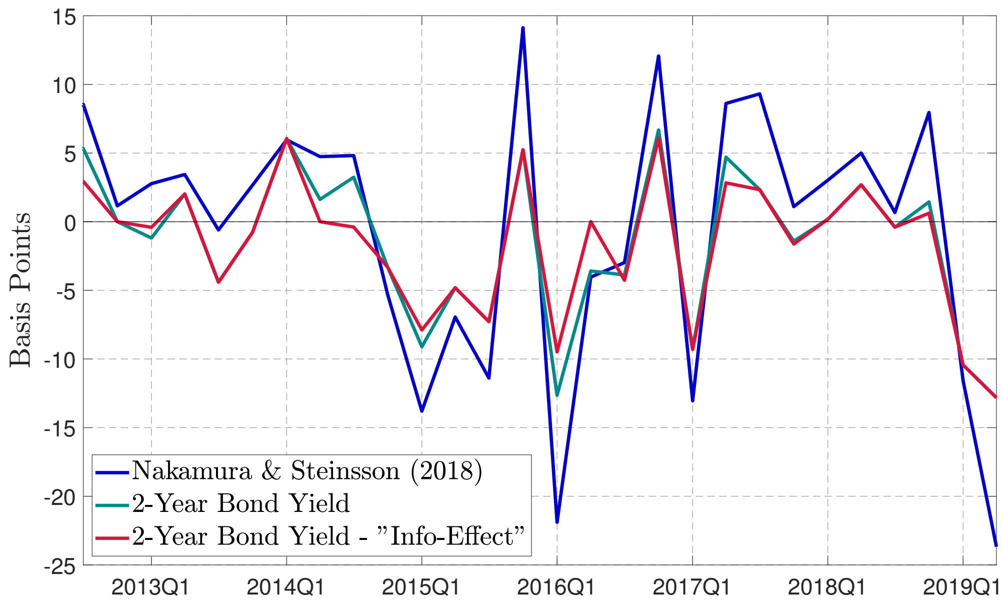


Figure E.1: Monetary Policy Surprises.

**Notes:** The figure shows monetary policy surprises that are measured within a 30-minute window around policy announcements of the Federal Reserve (10 minutes before and 20 minutes after each announcement) and aggregated to a quarterly frequency by summing up the individual surprises within a quarter (see also Romer and Romer, 2004, regarding the aggregation). The shock series displayed by the blue line follows the computations in Nakamura and Steinsson (2018) (see also footnote 66). The green line shows the surprises of the two-year government bond yield and the red line uses the same surprises but excludes the ones that are associated with nonstandard stock price responses following Jarociński and Karadi (2020). Sample: 2012:Q3 - 2019:Q2.

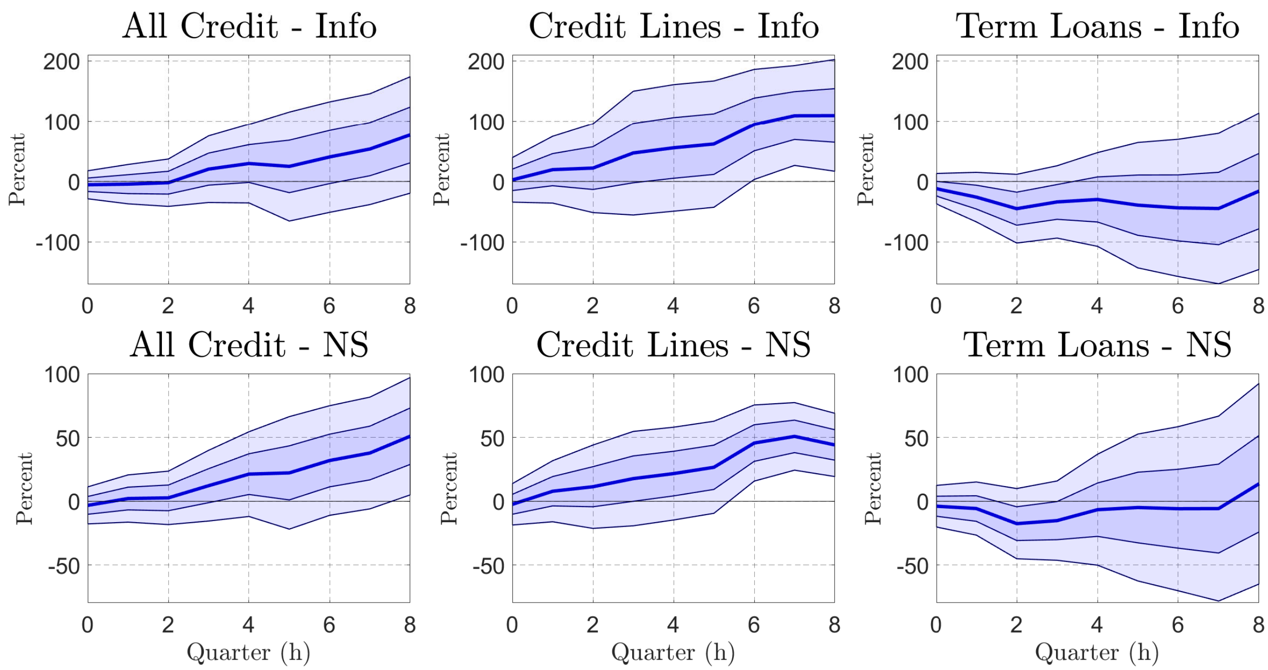


Figure E.2: "Information Effect" and Nakamura and Steinsson (2018)-surprises.

**Notes:** Impulse responses to a 100 basis point surprise increase in the two-year government bond yield that excludes surprises with nonstandard stock price responses (top graphs, "Info") and the shock series that follows the computations in Nakamura and Steinsson (2018) (bottom graphs, "NS", see also footnote 66). All estimations are based on the local projection approach in (5.1) that uses aggregated data, multiplied by 100. 95 and 68 percent confidence bands are shown using Newey and West (1987) standard errors. Sample: 2012:Q3 - 2019:Q2.

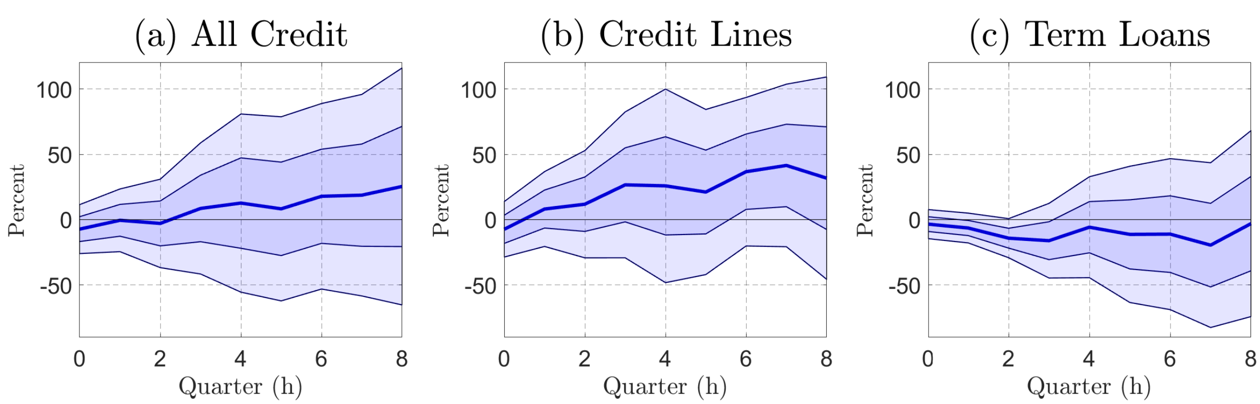


Figure E.3: Firm-Level Credit Responses to a Monetary Policy Surprise.

**Notes:** Impulse responses of firms' total used credit, credit lines, and term loans to a 100 basis point surprise increase of the two-year government bond yield based on the local projection approach in (5.2), multiplied by 100. The estimations are based on a balanced panel and include 235,225 observations for credit lines, 286,934 for term loans, and 498,384 for all credit for each impulse response horizon. 95 and 68 percent confidence bands are shown using Driscoll and Kraay (1998) standard errors. Sample: 2012:Q3 - 2019:Q2.

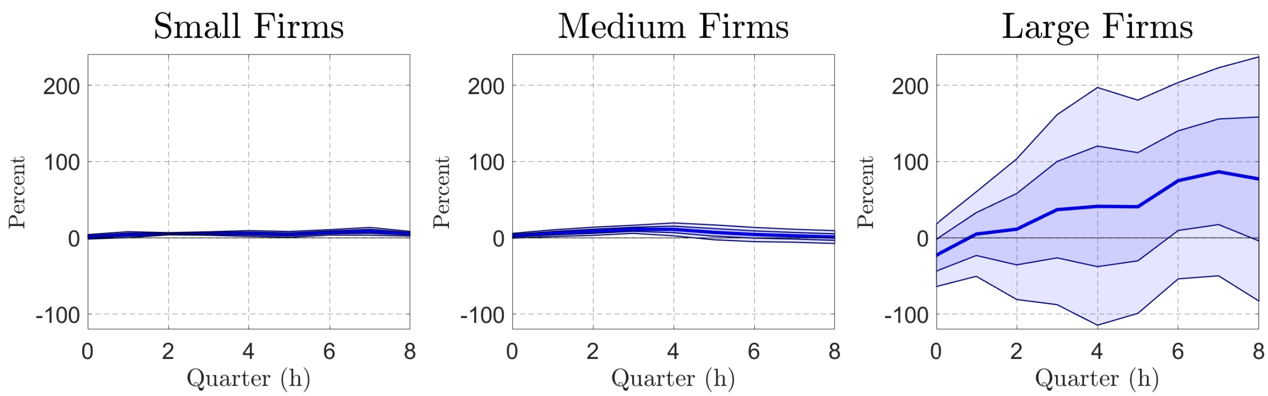


Figure E.4: Credit Line Responses by Firm Size.

**Notes:** Impulse responses of firms' credit lines to a 100 basis points surprise increase of the two-year government bond yield based on the local projection approach in (5.2), multiplied by 100. The estimations are based on a balanced panel and include a total of 88,941 observations for each respective impulse response horizon. Firms are separated into three bins of equal size according to their position along the firm size distribution in the quarter before the shock occurs. 95 and 68 percent confidence bands are shown using Driscoll and Kraay (1998) standard errors. Sample: 2012:Q3 - 2019:Q2.

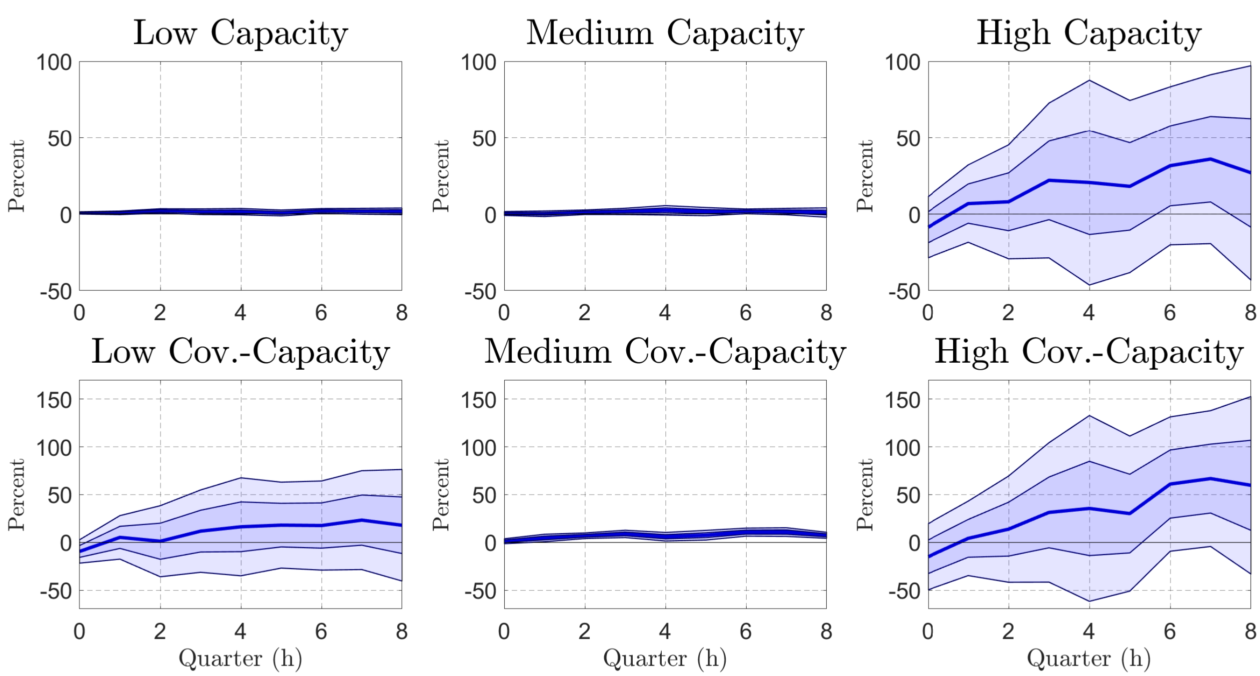


Figure E.5: Credit Line Responses by Borrowing Capacity.

**Notes:** Impulse responses of firms' credit lines to a 100 basis points surprise increase of the two-year government bond yield based on the local projection approach in (5.2), multiplied by 100. Firms are separated into three bins of similar size according to their position along the borrowing capacity distribution in the quarter before the shock occurs. The top graphs use firms' total unused borrowing as a measure of borrowing capacity, and the bottom graphs additionally adjust this measure for generic covenant rules (see Appendix B.2 for details). The estimations are based on a balanced panel and include a total of 235,225 observations (top figures), and 84,088 observations (bottom figures), respectively, for each impulse response horizon. 95 and 68 percent confidence bands are shown using Driscoll and Kraay (1998) standard errors. Sample: 2012:Q3 - 2019:Q2.

## E.2 Credit Supply Channels of Monetary Transmission

The positive credit responses to a contractionary monetary policy shock that are shown in Figures 1.2 and 5.1 do not necessarily imply that credit supply channels are absent. To illustrate that such effects are an important part of monetary transmission, we employ a fixed effect regression similar to Khwaja and Mian (2008). In particular, the methodology for estimating a credit supply channel focuses on firms' borrowing from multiple banks, where the banks differ in their exposure to a monetary policy shock. Following Gomez et al. (2020), we use banks' cash flow exposure to interest rate risk, measured using the so-called "income gap." The income gap ($IG_t^j$) for bank $j$ at time $t$ is defined as the value of book assets ($RA$) minus book liabilities ($RL$) that reprice or mature within the next year relative to total assets,

$$IG_t^j = \frac{RA_t^j - RL_t^j}{Total\ Assets_t^j} \quad ,$$

and we obtain an empirical measure of the income gap from the Consolidated Financial Statements or FR Y-9C filings for Bank-Holding Companies (see Table B.5 in Appendix B for details). Intuitively, banks with a higher income gap, that is more assets relative to liabilities that reprice over the next year, should experience a relatively higher cash flow and expand credit by more to a monetary tightening.

To obtain a data set of firms with multiple bank relations, we take the following steps. First, we consolidate all used credit of a particular type from the same bank to the same firm. In particular, we classify loans into types according to whether they are variable- or fixed-rate loans and whether they are term loans or credit lines.[72] Second, we exclude all observations in which a firm obtains several types of credit from the same bank. Third, we exclude all firms that only hold credit of a particular type from one bank at some date. Based on the resulting data set, we estimate

$$\frac{L_{i,t+h}^{j,k} - L_{i,t-1}^{j,k}}{0.5\left(L_{i,t+h}^{j,k} + L_{i,t-1}^{j,k}\right)} = \alpha_{i,t}^{k,h} + \beta^h \epsilon_t^{MP} \cdot IG_{t-1}^j + \gamma^h IG_{t-1}^j + u_{i,t}^{j,k,h} \quad , \tag{E.1}$$

for $h = 0, 1, .., 3$, using the same formulation for the dependent variable as in Section 4.2, which allows for possible zero-observations in $t-1$ or $t$ and is bounded in the range $[-2,2]$. $L_{i,t}^{j,k}$ denotes the loan amount of type $k$ between bank $j$ and firm $i$ at time $t$ and $\alpha_{i,t}^{k,h}$ is a firm-time-specific fixed effect for credit type $k$ and impulse response horizon $h$. This fixed effect captures the firm's credit demand that is common for loan type $k$ between time $t$ and $t+h$, as explained further below. The coefficient of interest is $\beta^h$ on the interaction

[72]Besides term loans and credit lines, we also consider variable- and fixed-rate loans as separate types since changes in short-term rates from one period to the next have a differential impact on the cost and possibly on the demand for such loans.

term $\epsilon_t^{MP} \cdot IG_{t-1}^j$, where $\epsilon_t^{MP}$ denotes a monetary policy shock at time $t$ and $IG_{t-1}^j$ is bank $j's$ income gap in the quarter before the shock occurs, which is also included as an additional control.

Given the near-term focus of the income gap, we estimate impulse responses up to $h = 3$ and use the monetary policy shock series by Nakamura and Steinsson (2018), which loads more heavily on the short end of the yield curve compared with the two-year government bond yield surprise that is used in Section 5.1 (see also footnote 66). Moreover, we narrow the data set in two additional ways. First, we require that firms have at least three banking relationships for a particular credit type $k$ at some date. Second, the magnitude of the changes of the dependent variable depend on the loan amount in $t-1$ and certain loan responses may therefore simply differ because of their different starting levels. To avoid the estimations being affected by such differences, we restrict the loan amounts to be of similar size in $t-1$. In particular, we require that the share of some loan relative to the sum of all the firm's loans of this type is not smaller than $1/(2 \cdot N)$, where $N$ is the number of loans that a firm possesses of this type. Otherwise all firm-credit-type observations are excluded.

Given the setup of the data set and regressions (E.1), the identifying assumption is that firms treat banks equally when deciding on their credit needs, such that the fixed effect $\alpha_{i,t}^{k,h}$ soaks up a firm's credit demand. The estimated coefficients $\beta^h$ should therefore capture credit supply effects: depending on their differential exposure to the monetary policy shock, banks may differ in their credit supply to firms. Figure E.6 shows the estimated coefficients $\beta^h$. Confirming the intuition above, the coefficients have a positive sign and they are statistically significant at the two standard-deviation confidence intervals for the one-quarter ahead impulse response horizon. That is, banks with a larger income gap expand credit by more when monetary policy tightens. These results are in line with the findings in Gomez et al. (2020) and show that credit supply effects are not absent for the responses that are shown in Figures 1.2 and 5.1. In unreported results, we check and confirm that the results are robust to a range of changes to the baseline setup: decreasing or increasing the minimum number of banking relationships to 2 or 4, excluding firms with multiple credit types or credit lines, including the same bank-specific controls as in Table 5.1, using the two-year government bond yield surprise or the federal funds target change as a measure of the monetary policy shock, tightening or easing the restriction on the equality of loan amounts to $1/(1.5 \cdot N)$ or $1/(3 \cdot N)$, using $\left(L_{i,t+h}^{j,k} - L_{i,t-1}^{j,k}\right)/L_{i,t-1}^{j,k}$ as a dependent variable in (E.1), or changing the starting date to 2014:Q1, given that the quarters before show few revisions to expectations about the near-term path of monetary policy.

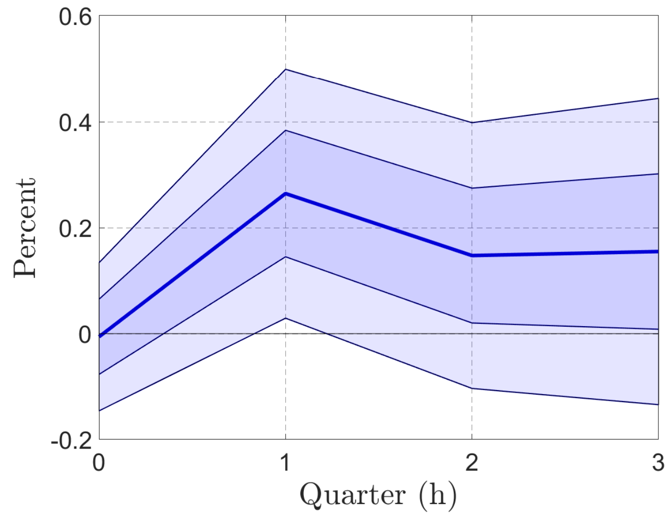


Figure E.6: Credit Supply Effects.

**Notes:** The figure shows the estimated coefficient $\hat{\beta}^h$ based on the regression setup (E.1). The estimations for each impulse response horizon are based on approximately 12,000 firm-credit-type observations with at least three banking relationships. 95 and 68 percent confidence bands are shown using standard errors that are clustered by bank. Sample: 2012:Q3 - 2019:Q2.

## E.3 Credit Movements around COVID-19

To further understand which firms accounted for the drawdowns on existing credit lines and how those firm characteristics changed relative to other periods, we estimate a set of regressions,

$$Y_{i,t} = \alpha_t + \tau_k + \boldsymbol{\beta_1 X_{i,t-1}} + \boldsymbol{\beta_2 X_{i,t-1}} \cdot I_t + u_{i,t} \quad , \tag{E.2}$$

where $X_{i,t-1}$ is a vector of firm characteristics, $I_t$ is an indicator variable that is equal to one in 2020:Q1 and zero otherwise, and $Y_{i,t}$ is one of three possible dependent variables. First, it is given by the log-odds ratio of a $\{0-1\}$-indicator, determining whether a firm draws on an existing credit line from one quarter to the next (column (i) of Table E.1). Along the intensive margin, column (ii) considers the change in the use of an existing credit line, where the functional form is again given by $2 \cdot (L_{i,t} - L_{i,t-1}) \,/\, (L_{i,t} + L_{i,t-1})$ to account for possible zero observations and diminish the influence of extreme observations. We also specify a change of an existing credit line measure that is scaled by lagged average credit line use across all firms as a way of detecting which type of firms account for the aggregate change in utilization, $(L_{i,t} - L_{i,t-1}) \,/ \overline{L}_{t-1}$ (column (iii) in Table E.1).[73] Besides the time- and industry-fixed effects $\alpha_t$ and $\tau_k$, the same set of explanatory variables is used as in Section 4.1, apart from using net income instead of EBITDA as a measure of profitability.[74] The interaction terms are intended to uncover whether the usual financing patterns may have changed in 2020:Q1.

Similar to the findings in Section 4.2, the negative coefficient on "Net Income" suggests that firms draw on their credit lines when they experience low profits in normal times. However, at the onset of the pandemic, this relationship flips, such that previously profitable firms access their credit lines. A similar pattern occurs for the variables "Size" and "Public," as well as for "Borrowing Capacity" at the extensive margin. Thus, in 2020:Q1, the type of firms that access their existing credit lines are different compared with an economy in normal times: large, profitable, publicly traded firms with preestablished borrowing capacity draw on their available funding. In addition, more highly leveraged firms and firms rated below investment grade are generally more likely to use their credit lines.

In Table E.2, we additionally report results from versions of regression E.2 estimated for new credit issuances. Firms without preestablished borrowing likely have a stronger need for new credit, which is confirmed by the negative coefficients on "Borrowing Capacity" at the extensive margins in columns (i) and (ii). However, once a firm obtains

[73] $L_{i,t}$ and $L_{i,t-1}$ in columns (ii) and (iii) of Table E.1 denote credit lines that were established in $t-1$ or prior to that date. $\overline{L}_{t-1}$ is the average credit line use across all firms in $t-1$, that is, $\overline{L}_{t-1} = (1/N)\sum_{i=0}^{N} L_{i,t-1}$.

[74] To eliminate outliers and data entry errors, observations within the 1 percent tails of the distributions for net income, tangible assets (both relative to noncash assets), and leverage are excluded.

new credit, the amount that is acquired is positively related to preestablished borrowing capacity, as shown in columns (iii) and (iv). For credit lines, the magnitude of this relation strongly increases for 2020:Q1.

Similar intensified effects for either credit lines or term loans in 2020:Q1 are visible for "Size," "Public," "Investment Grade," and "Firm Age": larger, publicly traded, highly rated, and older firms obtained more new credit in 2020:Q1 relative to other periods, all proxying firms' creditworthiness. The only exception to this pattern is "Leverage," for which we find an intensified positive relation in 2020:Q1.

Table E.1: COVID-19 − Changes in Existing Credit Lines.

| | (i) Draw Existing Line (0,1)-Dummy | | (ii) Δ Existing Line $2 \cdot (L_{i,t} - L_{i,t-1})/(L_{i,t} + L_{i,t-1})$ | | (iii) Δ Existing Line $(L_{i,t} - L_{i,t-1})/\overline{L}_{t-1}$ | |
|---|---|---|---|---|---|---|
| | Coeff. | Std.Err. | Coeff. | Std.Err. | Coeff. | Std.Err. |
| Borrowing Capacity | -0.33*** | 0.02 | 0.70*** | 0.01 | 0.85*** | 0.02 |
| $\cdot \times I_t$ | 0.77*** | 0.06 | 0.79*** | 0.03 | 1.46*** | 0.21 |
| Net Income | -0.05* | 0.03 | -0.05*** | 0.01 | -0.15*** | 0.01 |
| $\cdot \times I_t$ | 0.39*** | 0.10 | 0.19*** | 0.05 | 1.27*** | 0.23 |
| Tangible Assets | -0.78*** | 0.02 | 0.07*** | 0.01 | -0.00 | 0.01 |
| $\cdot \times I_t$ | -0.30*** | 0.08 | 0.04 | 0.04 | -0.08 | 0.28 |
| Size | -0.02*** | 0.00 | 0.00*** | 0.00 | -0.08*** | 0.00 |
| $\cdot \times I_t$ | 0.08*** | 0.01 | 0.04*** | 0.01 | 0.86*** | 0.10 |
| Leverage | 0.80*** | 0.03 | 0.12*** | 0.01 | 0.11*** | 0.02 |
| $\cdot \times I_t$ | -0.10 | 0.09 | -0.06 | 0.05 | 2.06*** | 0.41 |
| Investment Grade | -0.16*** | 0.01 | -0.03*** | 0.00 | -0.05*** | 0.01 |
| $\cdot \times I_t$ | 0.01 | 0.05 | 0.03 | 0.02 | 0.03 | 0.25 |
| Public | -0.14*** | 0.03 | -0.11*** | 0.01 | -0.37*** | 0.04 |
| $\cdot \times I_t$ | 0.35*** | 0.08 | 0.12*** | 0.04 | 5.90*** | 0.76 |
| Firm Age | 0.01 | 0.01 | -0.01*** | 0.00 | -0.02*** | 0.01 |
| $\cdot \times I_t$ | -0.02 | 0.02 | -0.01 | 0.01 | 0.06 | 0.15 |
| Sum of Coefficients 2020:Q1 | | | | | | |
| Borrowing Capacity | 0.44*** | 0.06 | 1.50*** | 0.03 | 2.31*** | 0.21 |
| Net Income | 0.34*** | 0.10 | 0.15*** | 0.05 | 1.12*** | 0.23 |
| Tangible Assets | -1.08*** | 0.08 | 0.11*** | 0.04 | -0.08 | 0.28 |
| Size | 0.05*** | 0.01 | 0.04*** | 0.01 | 0.79*** | 0.10 |
| Leverage | 0.70*** | 0.09 | 0.07 | 0.05 | 2.17*** | 0.41 |
| Investment Grade | -0.15*** | 0.05 | -0.01 | 0.02 | -0.02 | 0.25 |
| Public | 0.22*** | 0.08 | 0.02 | 0.04 | 5.54*** | 0.76 |
| Firm Age | -0.02 | 0.02 | -0.02** | 0.01 | 0.04 | 0.15 |
| R-squared | 0.04 | | 0.07 | | 0.03 | |
| Observations | 551,506 | | 385,194 | | 551,506 | |
| Number of Firms | 41,484 | | 33,788 | | 41,484 | |

**Notes:** Estimation results for firm credit regressions (E.2) using changes in existing credit lines from one quarter to the next. Dependent variables are a {0,1}-variable measuring whether a firm drew on an existing credit line in column (i), the change in used credit of an existing credit line, relative to a firm's own stock over two quarters in column (ii) or the average existing credit line stock in the previous quarter in column (iii). All explanatory variables are given by the most recent observations over the previous four quarters. Borrowing capacity is the share of unused borrowing to total commitments. Net income and tangible assets are scaled by noncash assets (total assets minus cash and marketable securities). Size is defined as the natural log of noncash asssets. Leverage is the ratio of total liabilities to total assets. Firm age is the natural log of the number of periods between the observation date and firm incorporation date, annualized. The incidence of a firm drawing on an existing credit line is estimated as a logit regression, reporting a Pseudo $R^2$. All other specifications are estimated using OLS. All estimations include time and industry fixed effects. Standard errors in parentheses are clustered by firm. Sample: 2012:Q3 - 2020:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.2: COVID-19 − Changes in New Credit.

| | (i) New Credit Line (0,1)-Dummy | | (ii) New Term Loan (0,1)-Dummy | | (iii) Δ New Credit Line $(L_{i,t} - L_{i,t-1})/\overline{L}_{t-1}$ | | (iv) Δ New Term Loan $(L_{i,t} - L_{i,t-1})/\overline{L}_{t-1}$ | |
|---|---|---|---|---|---|---|---|---|
| | Coeff. | Std.Err. | Coeff. | Std.Err. | Coeff. | Std.Err. | Coeff. | Std.Err. |
| Borrowing Capacity | -1.15*** | 0.02 | -0.30*** | 0.04 | 1.64*** | 0.13 | 0.09 | 0.14 |
| $\cdot \times I_t$ | 0.15 | 0.14 | 0.13 | 0.16 | 3.68*** | 1.24 | 0.88 | 0.97 |
| Net Income | 0.23*** | 0.04 | 0.64*** | 0.05 | -0.07 | 0.08 | 0.08 | 0.14 |
| $\cdot \times I_t$ | 0.08 | 0.24 | 0.27 | 0.19 | 0.27 | 1.16 | 1.20 | 1.55 |
| Tangible Assets | -0.73*** | 0.03 | -0.83*** | 0.05 | -0.10 | 0.11 | 0.27 | 0.18 |
| $\cdot \times I_t$ | -0.00 | 0.18 | 0.12 | 0.18 | -0.69 | 1.70 | 0.68 | 2.70 |
| Size | 0.05*** | 0.01 | 0.18*** | 0.01 | -0.09*** | 0.02 | 0.03 | 0.04 |
| $\cdot \times I_t$ | 0.04* | 0.03 | 0.05** | 0.02 | 0.49 | 0.43 | 1.58*** | 0.58 |
| Leverage | 0.58*** | 0.05 | 0.55*** | 0.06 | 0.18* | 0.11 | -0.55** | 0.22 |
| $\cdot \times I_t$ | 0.23 | 0.23 | 0.05 | 0.23 | 5.96** | 2.74 | 3.13* | 1.86 |
| Investment Grade | -0.01 | 0.02 | -0.11*** | 0.03 | -0.02 | 0.09 | 0.15 | 0.12 |
| $\cdot \times I_t$ | -0.00 | 0.12 | 0.05 | 0.11 | 3.07** | 1.45 | -0.38 | 1.98 |
| Public | 0.55*** | 0.04 | 0.25*** | 0.06 | 0.21 | 0.17 | 0.64** | 0.31 |
| $\cdot \times I_t$ | -0.25 | 0.16 | 0.23* | 0.13 | 8.15 | 4.99 | 11.12** | 5.56 |
| Firm Age | -0.01 | 0.01 | 0.05*** | 0.02 | -0.00 | 0.03 | -0.15 | 0.12 |
| $\cdot \times I_t$ | -0.07 | 0.06 | 0.01 | 0.06 | 1.70* | 0.95 | 3.33* | 1.78 |
| Sum of Coefficients 2020:Q1 | | | | | | | | |
| Borrowing Capacity | -1.01*** | 0.13 | -0.17*** | 0.16 | 5.32*** | 1.23 | 0.97 | 0.97 |
| Net Income | 0.31 | 0.24 | 0.91 | 0.19 | 0.20 | 1.16 | 1.27 | 1.51 |
| Tangible Assets | -0.73*** | 0.18 | -0.71*** | 0.18 | -0.79 | 1.68 | 0.95 | 2.64 |
| Size | 0.09*** | 0.02 | 0.23*** | 0.02 | 0.40 | 0.43 | 1.61*** | 0.57 |
| Leverage | 0.81*** | 0.23 | 0.60*** | 0.24 | 6.14** | 2.73 | 2.59 | 1.8 |
| Investment Grade | -0.01 | 0.12 | -0.05 | 0.11 | 3.06** | 1.44 | -0.23 | 1.95 |
| Public | 0.30* | 0.16 | 0.49* | 0.13 | 8.36* | 4.95 | 11.76** | 5.45 |
| Firm Age | -0.08 | 0.06 | 0.07 | 0.06 | 1.7* | 0.93 | 3.19* | 1.68 |
| R-squared | 0.08 | | 0.06 | | 0.00 | | 0.00 | |
| Observations | 551,506 | | 551,506 | | 551,506 | | 551,506 | |
| Number of Firms | 41,484 | | 41,484 | | 41,484 | | 41,484 | |

**Notes:** Estimation results for firm credit regressions (E.2). Dependent variables are a {0,1}-variable measuring whether a firm obtained a new credit line or term loan (positive used credit amount, columns (i) and (ii)) and the change in new used credit from one quarter to the next (columns (iii) and (iv)), relative to the average newly used credit in the previous quarter. All control variables are the most recent observations over the previous four quarters. Borrowing capacity is given by the share of unused borrowing to total commitments. Net income and tangible assets are scaled by noncash assets (total assets minus cash and marketable securities). Size is defined as the natural log of non-cash asssets. Leverage is the ratio of total liabilities to total assets. Observations within the one percent tails for net income, tangible assets, and leverage are excluded. Firm age is the natural log of number of periods between the observation date and firm incorporation date, annualized. The incidence of a firm obtaining new credit is estimated as a logit regression, reporting a Pseudo $R^2$. All other specifications are estimated using OLS. All estimations include time and industry fixed effects. Standard errors in parentheses are clustered by firm. Sample: 2012:Q3 - 2020:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.3: COVID-19 − Credit Supply in 2020:Q2.

| | (i) 2020:Q2 | (ii) 2020:Q2 | (iii) 2020:Q2 | (iv) 2020:Q2 | (v) 2020:Q1 |
|---|---|---|---|---|---|
| Δ Credit Line Usage | -2.60** | -2.72** | -4.05*** | -2.32** | -2.00*** |
| | (1.02) | (1.00) | (1.24) | (0.88) | (0.66) |
| Δ Deposits | | | | 0.18 | |
| | | | | (0.25) | |
| Fixed Effects | | | | | |
| Firm × Rate | ✓ | | | ✓ | ✓ |
| Firm × Rate × Maturity | | ✓ | | | |
| Firm × Rate × Purpose | | | ✓ | | |
| Bank Controls | | | ✓ | ✓ | |
| R-squared | 0.51 | 0.52 | 0.54 | 0.51 | 0.51 |
| Observations | 1,490 | 1,445 | 898 | 1,454 | 1,677 |
| Number of Firms | 670 | 650 | 414 | 656 | 748 |
| Number of Banks | 28 | 28 | 26 | 26 | 28 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q2 in columns (i)-(iv) and from 2019:Q4 to 2020:Q1 in column (v). 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). 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 liabilities), and banks' income gap (see Table B.5 in Appendix 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 E.4: COVID-19 Credit Supply − Sample Splits in 2020:Q1.

| | (i) Fixed-Rate | (ii) Adj.-Rate | (iii) Small Loans | (iv) Large Loans | (v) Non-Synd. | (vi) Synd. |
|---|---|---|---|---|---|---|
| Δ Credit Line Usage | -2.59*** | -0.06 | -1.99*** | -0.10 | -2.35*** | -0.13 |
| | (0.87) | (0.85) | (0.61) | (1.52) | (0.76) | (1.89) |
| Fixed Effects | | | | | | |
| Firm | ✓ | ✓ | | | | |
| Firm × Rate | | | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.49 | 0.6 | 0.5 | 0.61 | 0.47 | 0.78 |
| Observations | 1,308 | 369 | 1,269 | 167 | 1,376 | 187 |
| Number of Firms | 585 | 167 | 572 | 78 | 617 | 82 |
| Number of Banks | 22 | 26 | 26 | 22 | 23 | 21 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q1. 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 percent and the top 10 percent of the unconditional loan size distribution in 2019:Q4. Columns (v) and (vi) split the sample into non-syndicated and syndicated loans. All specifications are estimated using OLS. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.5: COVID-19 Credit Supply − Sample Splits in 2020:Q2.

| | (i) Fixed-Rate | (ii) Adj.-Rate | (iii) Small Loans | (iv) Large Loans | (v) Non-Synd. | (vi) Synd. |
|---|---|---|---|---|---|---|
| Δ Credit Line Usage | -3.63** | 0.86 | -3.25** | 1.38* | -3.19** | -0.23 |
| | (1.39) | (1.03) | (1.17) | (0.68) | (1.24) | (2.01) |
| Fixed Effects | | | | | | |
| Firm | ✓ | ✓ | | | | |
| Firm × Rate | | | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.51 | 0.58 | 0.5 | 0.87 | 0.49 | 0.65 |
| Observations | 1,174 | 316 | 1,120 | 150 | 1,233 | 163 |
| Number of Firms | 531 | 142 | 511 | 70 | 560 | 71 |
| Number of Banks | 22 | 26 | 25 | 21 | 23 | 20 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q2. 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 percent and the top 10 percent of the unconditional loan size distribution in 2019:Q4. Columns (v) and (vi) split the sample into non-syndicated and syndicated loans. 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 E.6: COVID-19 Credit Supply − Fixed Effects.

| | (i) 2020:Q1 | (ii) 2020:Q1 | (iii) 2020:Q1 | (iv) 2020:Q2 | (v) 2020:Q2 | (vi) 2020:Q2 |
|---|---|---|---|---|---|---|
| Δ Credit Line Usage | -0.35 | -0.42** | -0.64** | -1.07*** | -0.99*** | -1.10*** |
| | (0.22) | (0.18) | (0.27) | (0.30) | (0.33) | (0.32) |
| Fixed Effects | | | | | | |
| Rate | ✓ | ✓ | | ✓ | ✓ | |
| Rate × Industry × Location | | | ✓ | | | ✓ |
| Single Lender | | ✓ | | | ✓ | |
| R-squared | 0.00 | 0.00 | 0.43 | 0.00 | 0.00 | 0.46 |
| Observations | 31,307 | 23,470 | 11,431 | 29,050 | 22,247 | 10,197 |
| Number of Firms | 28,623 | 23,470 | 9,596 | 26,772 | 22,247 | 8,642 |
| Number of Banks | 29 | 29 | 29 | 29 | 29 | 29 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is either given by changes in credit between 2019:Q4 and 2020:Q1 in columns (i)-(iii), or between 2019:Q4 and 2020:Q2 in columns (iv)-(vi). 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), (ii), (iv), and (v) include fixed effects that vary by rate type (adjustable- or fixed-rate). Columns (iii) and (vi) additionally allow the fixed effects to vary by industry (two-digit NAICS code) and location (zip code of a firm's headquarter). Columns (ii) and (iv) consider only firms with a single lender within our 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 E.7: COVID-19 − Credit Supply IV-estimation.

| | (i)<br>2020:Q1 | (ii)<br>2020:Q2 | (iii)<br>2020:Q1 | (iv)<br>2020:Q2 |
|---|---|---|---|---|
| Δ Credit Line Usage | -2.06* | -2.90* | -2.56** | -4.11** |
| | (1.09) | (1.56) | (0.98) | (1.72) |
| Fixed Effects | | | | |
| Firm × Rate | ✓ | ✓ | ✓ | ✓ |
| Non-Syndicated Loans | | | ✓ | ✓ |
| Bank Controls | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.51 | 0.51 | 0.47 | 0.5 |
| Observations | 1,649 | 1,464 | 1,350 | 1,209 |
| Number of Firms | 737 | 660 | 607 | 551 |
| Number of Banks | 27 | 27 | 22 | 22 |

**Notes:** Instrumental variable estimation results for regressions (5.3), where the dependent variable is either given by changes in credit between 2019:Q4 and 2020:Q1 in columns (i) and (iii), or between 2019:Q4 and 2020:Q2 in columns (ii) and (iv). 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. The F-test statistics from the various first-stage regressions are all larger than 30 and therefore above typical critical values testing for weak identification. Columns (iii) and (iv) restrict the sample to non-syndicated loans only. 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 liabilities), and banks' income gap (see Table B.5 in Appendix B.1 for details on the data). Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table E.8: COVID-19 Credit Supply − Probability of Default.

| | (i) 2020:Q1 | (ii) 2020:Q2 | (iii) 2020:Q1 | (iv) 2020:Q2 |
|---|---|---|---|---|
| Δ Credit Line Usage | -1.91*** | -2.44*** | -2.31*** | -3.16*** |
| | (0.61) | (0.83) | (0.64) | (0.98) |
| Δ Probability Default | 0.17 | -0.05 | 0.07 | -0.22 |
| | (0.45) | (0.83) | (0.57) | (0.96) |
| Δ Provision Losses | 4.55 | 7.49 | 5.84 | 4.64 |
| | (4.63) | (9.80) | (6.82) | (14.37) |
| Fixed Effects | | | | |
| Firm × Rate | ✓ | ✓ | ✓ | ✓ |
| Non-Syndicated Loans | | | ✓ | ✓ |
| Bank Controls | ✓ | ✓ | ✓ | ✓ |
| R-squared | 0.51 | 0.51 | 0.47 | 0.5 |
| Observations | 1,649 | 1,464 | 1,350 | 1,209 |
| Number of Firms | 737 | 660 | 607 | 551 |
| Number of Banks | 27 | 27 | 22 | 22 |

**Notes:** Estimation results for regressions (5.3), where the dependent variable is either given by changes in credit between 2019:Q4 and 2020:Q1 in columns (i) and (iii), or between 2019:Q4 and 2020:Q2 in columns (ii) and (iv). 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. 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. 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. Columns (iii) and (iv) restrict the sample to non-syndicated loans only. 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 liabilities), and banks' income gap (see Table B.5 in Appendix B.1 for details on the data). Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

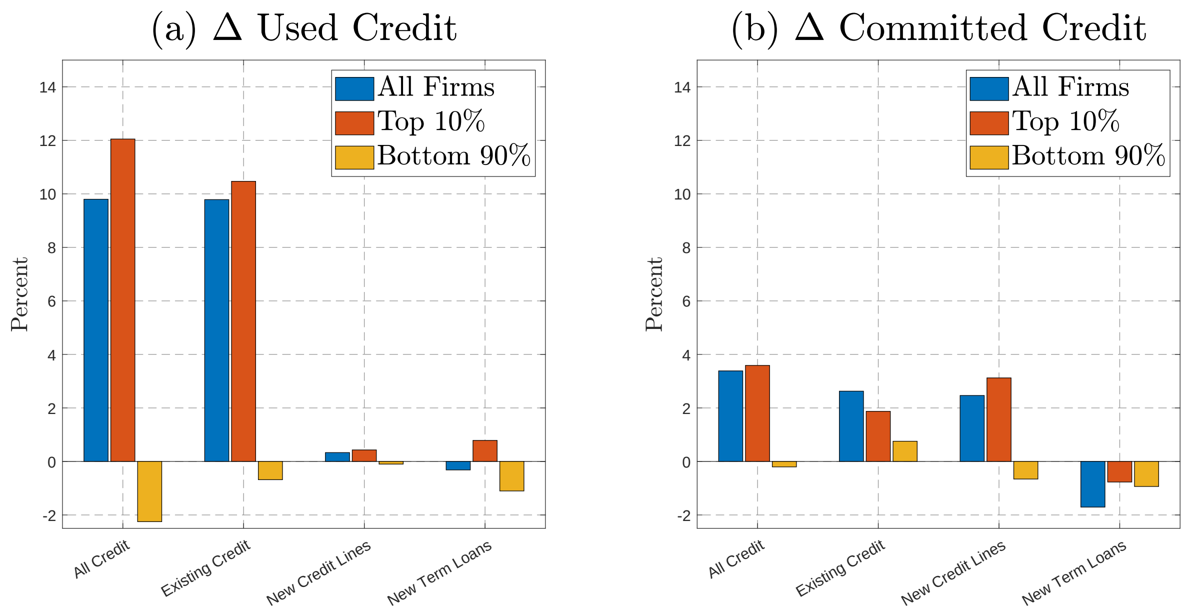


Figure E.7: Changes in Used and Committed Credit for 2019:Q4 - 2020:Q2.

**Notes:** The blue bars show aggregate changes in used and committed credit across all banks between 2019:Q4 and 2020:Q2, relative to total used credit in 2019:Q4. The orange and yellow bars display equivalent changes for the top 10 percent and the bottom 90 percent 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 for the two quarters. See Section 2 and Appendix B for details about the data.

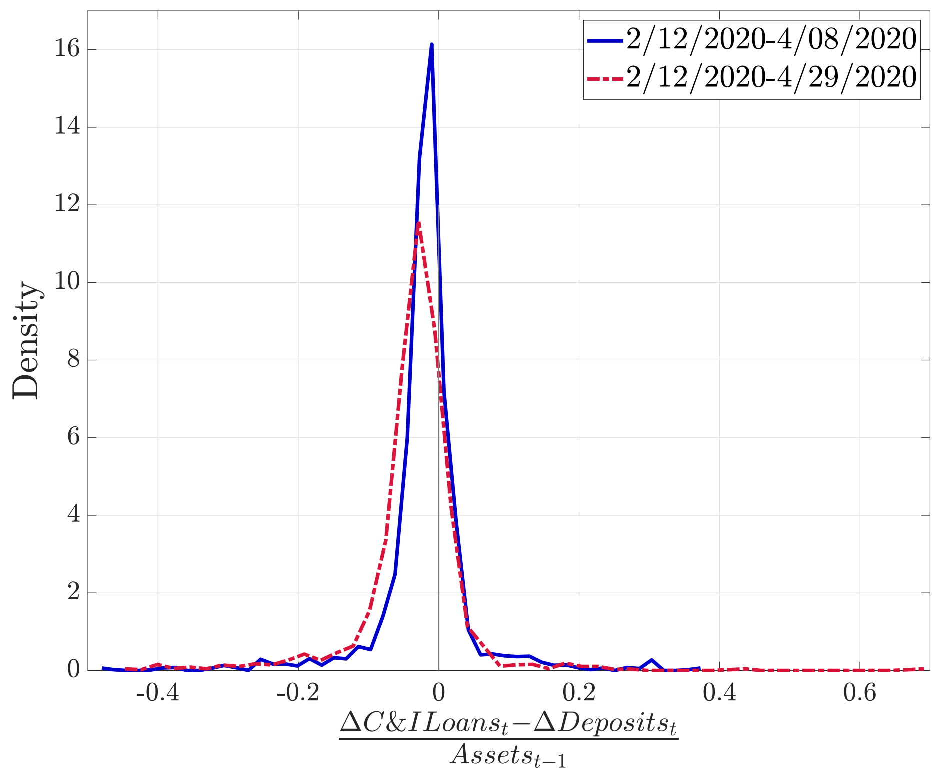


Figure E.8: U.S. commercial banks' balance sheets around the start of COVID-19.

**Notes:** The figure shows the kernel density of the difference between the change in C&I loans and the change in total deposits for the periods 2/12/2020-4/08/2020 and 2/12/2020-4/29/2020, relative to total assets on 2/12/2020, across U.S. commercial banks. The underlying data is obtained from the FR 2644 forms for U.S. commercial banks (a confidential bank-level version of the H.8 releases). The form can be found at: https://www.federalreserve.gov/reportforms/forms/FR_264420190327_f.pdf.

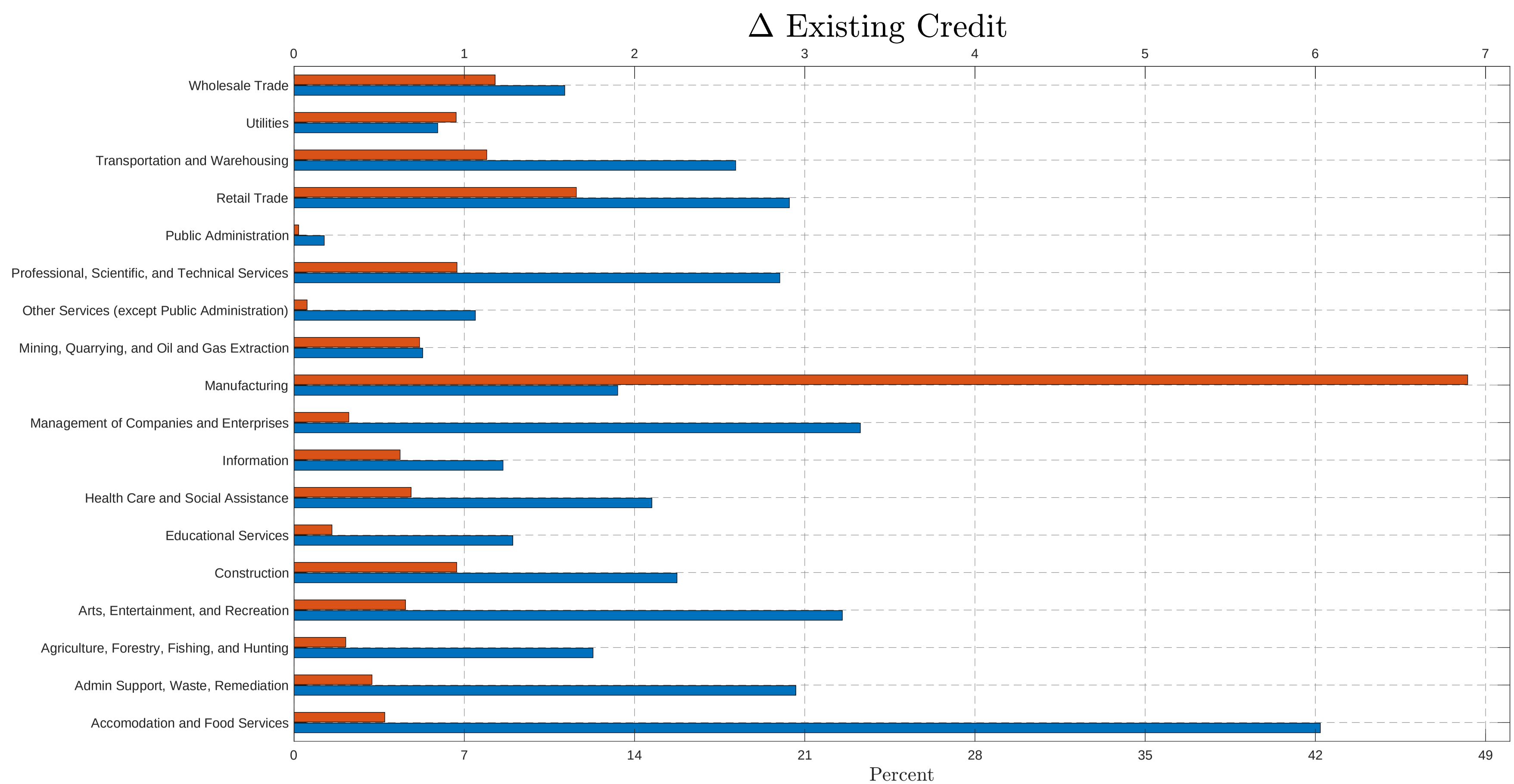


Figure E.9: Changes in Existing Credit for 2019:Q4 - 2020:Q1 by Industry.

**Notes:** The orange bars show changes in used existing credit between 2019:Q4 and 2020:Q1 by industry, relative to total used credit in 2019:Q4 across all firms and banks. The blue bars display the same change in used existing credit, but relative to total unused credit in 2019:Q4 of that industry. See Section 2 and Appendix B for details about the data.

# F Additional Model Results

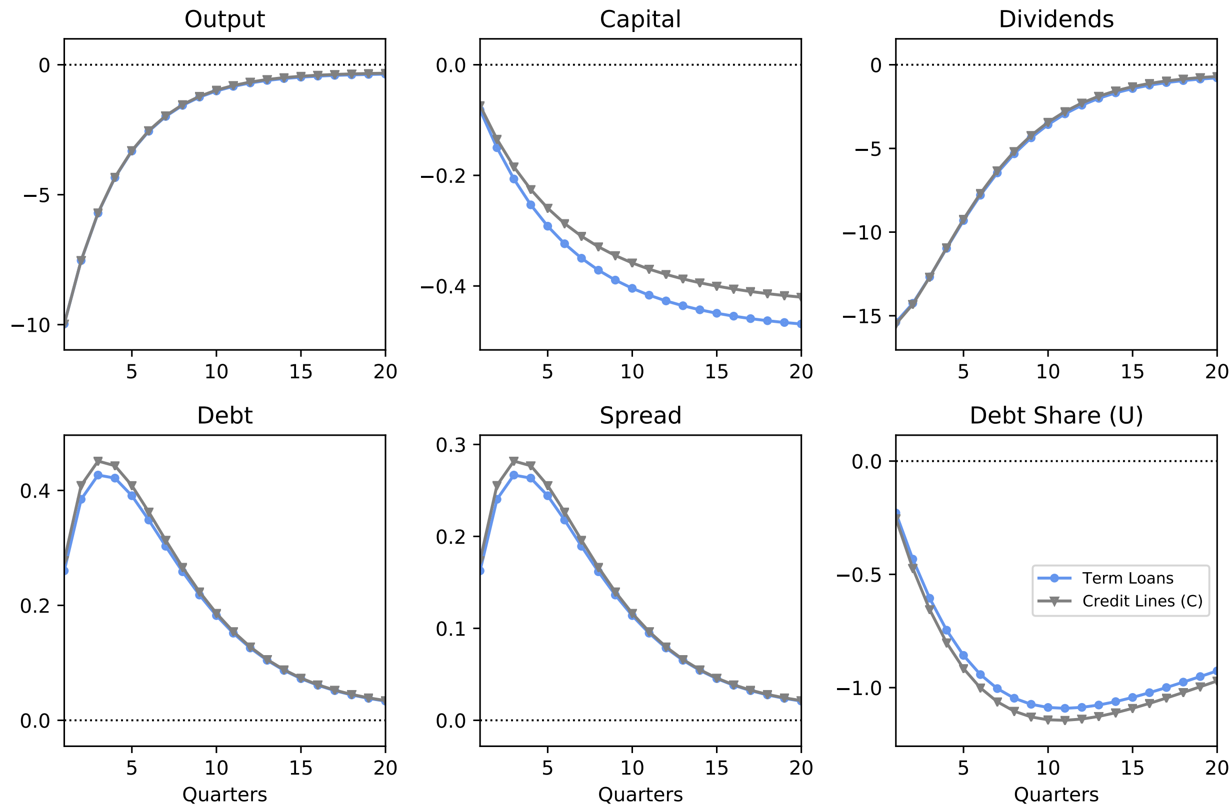


Figure F.1: Aggregate Responses, Counterfactual Credit Line Economies

**Notes:** This figure plots the impulse response to the productivity shock $\varepsilon_Z = -0.0552$. All variables are in logs and are displayed in percent.

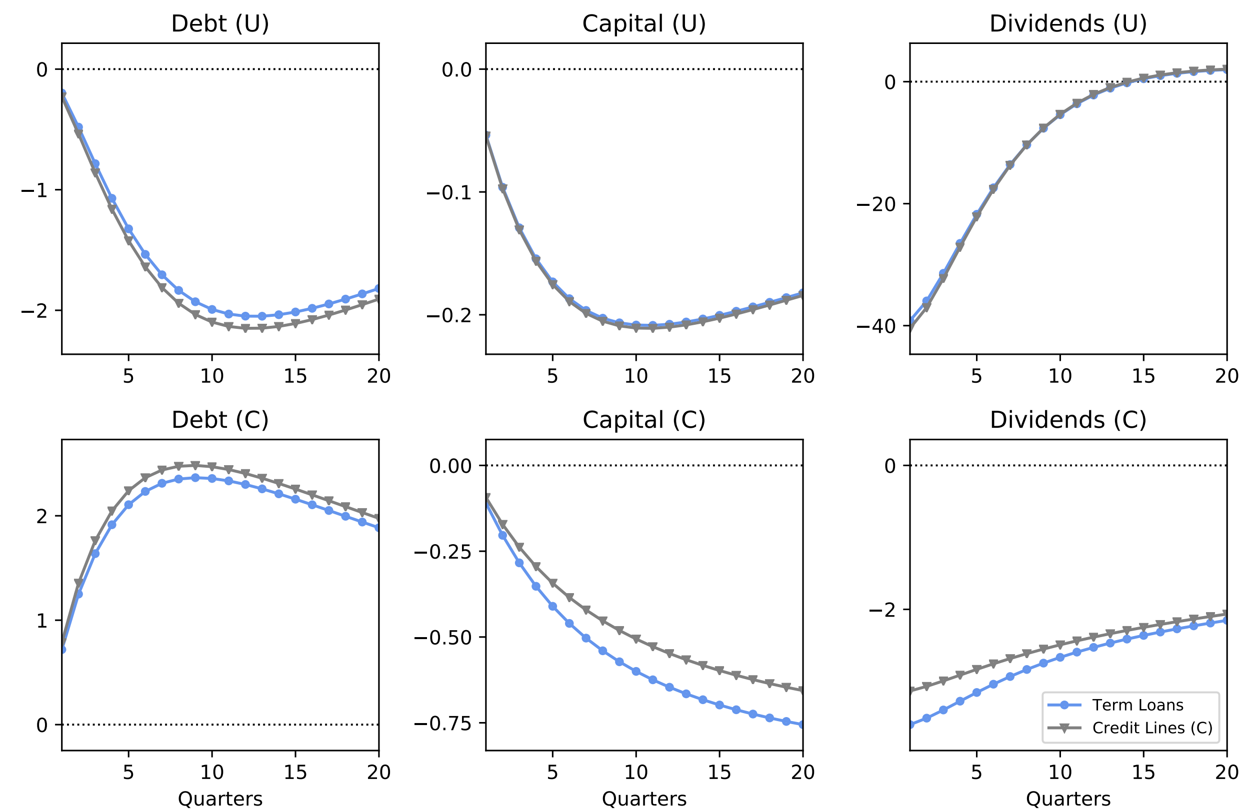


Figure F.2: Sector-Level Responses, Counterfactual Credit Line

**Notes:** This figure plots the impulse response to the productivity shock $\varepsilon_Z = -0.0552$. All variables are in logs, with the exception of Spread (defined as $s_{C,t}$, or $s_{U,t}$ for the All Unconstrained economy) and are displayed in percent.