NBER WORKING PAPER SERIES

BANK LIQUIDITY PROVISION ACROSS THE FIRM SIZE DISTRIBUTION

Gabriel Chodorow-Reich
Olivier Darmouni
Stephan Luck
Matthew C. Plosser

Working Paper 27945
http://www.nber.org/papers/w27945

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020, Revised December 2020

We thank Tania Babina, Tobias Berg, Xavier Giroud, Ivan Ivanov, Martina Jasova, Trish Mosser, Stijn Van Nieuwerburgh, Pascal Paul, Giorgia Piacentino, Kerry Siani, and seminar participants at the UC Berkeley Haas School of Business, Columbia Business School, the FDIC, John Hopkins University, the Temple Fox School of Business, and the University of Rochester Simon School of Business for useful comments and Sungmin An, Harry Cooperman, and Alena Kang-Landsberg for excellent research assistance. The opinions expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of New York, the Federal Reserve System, or the National Bureau of Economic Research.

Bank Liquidity Provision Across the Firm Size Distribution
Gabriel Chodorow-Reich, Olivier Darmouni, Stephan Luck, and Matthew C. Plosser
NBER Working Paper No. 27945
October 2020, Revised December 2020
JEL No. E51,G21,G32

ABSTRACT

We use supervisory loan-level data to document that small firms (SMEs) obtain shorter maturity credit lines than large firms; have less active maturity management; post more collateral; have higher utilization rates; and pay higher spreads. We rationalize these facts as the equilibrium outcome of a trade-off between lender commitment and discretion. Using the COVID recession, we test the prediction that SMEs are subject to greater lender discretion by examining credit line utilization. We show that SMEs do not drawdown in contrast to large firms despite SME demand, but that PPP loans helped alleviate the shortfall.

Gabriel Chodorow-Reich
Department of Economics
Harvard University
1805 Littauer Center
Cambridge, MA 02138
and NBER
chodorowreich@fas.harvard.edu

Olivier Darmouni
Columbia Business School
Uris 816
New York, NY 10027
omd2109@columbia.edu

Stephan Luck
Federal Reserve Bank of New York
33 Liberty St
New York, NY 10045
stephan.luck@ny.frb.org

Matthew C. Plosser
Financial Intermediation Function
Federal Reserve Bank of New York
33 Liberty Street
New York, NY 10045
matthew.plosser@ny.frb.org

1 Introduction

The ability of borrowers to access funds in bad times is crucial to avoiding financial distress, with banks playing a key role as liquidity providers (Kashyap et al., 2002; Gatev and Strahan, 2006). However, there are widespread concerns that small firms might not be able to access this liquidity, unlike firms at the top of the size distribution.[1] These concerns reflect the high reliance of small firms on bank funding and that they are riskier and more opaque than larger firms (Petersen and Rajan, 1994; Berger and Udell, 1995; Gertler and Gilchrist, 1994), so that financing may not materialize when it is most needed. And yet, empirical evidence of differential access to bank liquidity by small and medium enterprises (SMEs) remains scarce, as most analyses of loan terms in the United States rely on syndicated loan data that only includes large loans and by extension large borrowers.

In this paper we document sharp differences in the provision of bank liquidity to small and large firms. Using supervisory data covering 60% of all corporate loans, including to 50,000 SMEs, we present five facts about differences in loan terms that reflect lender *commitment* to large firms and *discretion* to small firms. Relative to large firms, small firms (i) obtain credit lines with much shorter maturity, (ii) have less active maturity management and as a result frequently have expiring credit, (iii) post more collateral, (iv) have higher utilization rates, and (v) pay higher spreads even conditional on other firm characteristics.

We then show that differences in loan terms impacted firms' access to liquidity at the outset of the COVID-19 recession. The increase in bank credit in 2020Q1 and 2020Q2 came almost entirely from drawdowns by large firms on pre-committed lines of credit, whereas small firms had no net drawdown of credit lines. To minimize differences in demand for credit in explaining these results, we further show that large firms exhibited much higher sensitivity of drawdown rates to industry-level measures of exposure to the COVID recession. Instead, differences in drawdowns appear to reflect deteriorating firm fundamentals and banks' ability to exercise discretion in lending to small firms. Finally, we analyze the role of the government-sponsored Paycheck Protection Program (PPP) in alleviating the liquidity shortfall to small firms. By merging the PPP data with our supervisory data, we find that PPP recipients on net *reduced* their non-PPP bank borrowing in 2020Q2, suggesting that the program fully overcame any shortfall but at a cost to the government.

[1] See e.g. "Much of America Is Shut Out of The Greatest Borrowing Binge Ever", August 13th 2020, *Bloomberg*, https://www.bloomberg.com/news/articles/2020-08-13/a-2-trillion-credit-boom-leaves-america-s-smaller-firms-behind (accessed September 8, 2020).

The paper unfolds as follows. Section 2 describes the supervisory data. The data come from the Federal Reserve Y-14 and contain information on all loans of more than $1 million made by banks with more than $100 billion in total consolidated assets. For each loan, the data contain information on loan terms (loan type, commitment, maturity, origination date, interest rate, collateral type, etc.) and borrower characteristics (industry, assets, sales, risk rating, etc.). We benchmark the Y-14 sample against the universe of corporate loans as well as loans to public firms (Compustat) and syndicated loans.

Section 3 presents an illustrative framework of equilibrium loan term determination to set the stage for the empirical analysis. We emphasize an incomplete contracting view of credit lines in the cross-section of firms. The framework extends the Holmström and Tirole (1998) model of liquidity provision to firms facing cash-flow shocks to allow for uncertainty over the borrower's final pledgable value. Loan terms give lenders either *commitment* or *discretion* in granting funds. With lender commitment, the borrower can always draw on credit limits determined ex-ante. With discretion the lender can deny requests for funds ex-post even though liquidity is available on paper. Both types of contracts reduce credit constraints: commitment through an insurance channel by cross-subsidizing high shocks with low shocks and discretion by giving the lender an option to monitor and make funding contingent on the borrower's repayment prospects. In equilibrium, firms choose contracts that minimize the probability of liquidity-driven default. Firms that choose discretion have pledgeable value that is (i) small relative to expected cash-flow shocks and (ii) more uncertain ex-ante. Intuitively, insurance is less valuable when large cash-flow shocks are more likely, and discretion more valuable when the option value of monitoring is larger. We provide evidence of audit frequency and firm volatility that links these characteristics to small firms.

Section 4 presents the five facts about bank loan terms across the firm size distribution. Fact 1 documents sharp differences in maturity at origination for credit lines, but not for other loan types. Among firms with less than $50 million in assets, three-quarters of credit lines have maturity of 1 year or less at origination and more than one-quarter of loans to these firms are demand loans immediately callable by the lender. These loans grant banks discretion — any time the borrower requests funds, the lender can monitor and reject. The share of credit lines with less than 1 year maturity at origination declines to below 10% for firms with more than $1 billion of assets, for which the median and modal credit line is a 5 year facility. The maturity difference disappears for term loans, for which the vast majority of credit to both small and large firms originates with 5 or more years of maturity. In our framework, term loans offer less scope for discretion since the bank disburses the funds up front.

Fact 2 shows that all firms actively manage the maturity of long-term loans but not of short-term loans, leaving a sizable share of credit lines to small firms requiring rollover. Across the firm size distribution, the median renewal of a loan with more than 4 years of maturity at origination occurs with more than three years of maturity remaining. On the other hand, loans with 1 year of maturity at origination simply get rolled over as they become due. Because the smallest firms in our data overwhelmingly have short-term credit lines (fact 1), this pattern yields a sizable share of small firms in any month with callable or expiring credit lines. For example, more than 80% of credit lines outstanding to the smallest firms at the end of 2019 were immediately callable or matured sometime in 2020. In contrast, only 15% of credit lines to the largest firms had less than 1 year of maturity remaining, and the median loan had around 3 years of maturity remaining. The frequent expiration of credit lines to small firms gives lenders the threat point to not rollover in negotiating with borrowers who want to draw funds.

Fact 3 establishes differences in collateral requirements across the firm size distribution. Less than 5% of credit lines to small firms are unsecured. The modal credit line to a firm in this size class is secured by accounts receivable and inventory (AR&I). AR&I is a particularly fragile type of collateral since lenders can choose to monitor and revalue it at any time and deny requests for funds that exceed the collateral value. The share unsecured rises with firm size, up to 70% of credit lines to firms with more than $5 billion in assets. Large differences in the share unsecured also emerge for term loans, but for secured loans the collateral type differs from that backing credit lines. For the smallest firms, half of term loans have real estate backing, while for larger firms, fixed assets become more prevalent.

Fact 4 shows that in normal times small firms have higher and more variable utilization rates on their credit lines. At the end of 2019, nearly one-fifth of small SMEs had a credit line utilization rate above 90% and one-third had a utilization rate above 70%. Conversely, only 7% of the largest firms had a utilization rate above 70%, and three-quarters of these firms had utilization rates below 10%. The high and variable utilization by small firms suggest that in normal times contracts with discretion mostly allow small firms to access liquidity when needed.

Fact 5 covers loan pricing. Despite the shorter maturity on credit lines, less active liquidity management, and higher collateral requirements, small firms nonetheless pay higher spreads than large firms. Differences in industry, lender, firm financials, and the lender's internal rating of the firm explain about one-third of the size gradient. This evidence suggests that small firms have different characteristics, including "soft" information such as quality of financial reporting, that lead them to choose contracts with discretion.

Section 5 turns to the provisioning of credit to small and large firms following the COVID-19 cash-flow shock. Total outstanding C&I loans increased sharply in the first quarter of 2020. We first show that this overall increase almost entirely comprises of higher drawdowns of pre-existing credit lines by large firms, a point conjectured in Li et al. (2020) and documented in independent work by Greenwald et al. (2020). The higher drawdown rate at larger firms survives controls for lender and borrower industry, state, leverage, profitability, rating, cash holdings, and bond market access in a difference-in-difference framework that interacts firm size category and each of these controls with an indicator for post-2020Q1. Controlling for loan maturity and collateral type interacted with the post indicator reduces the size gradient, consistent with more stringent terms to small firms restricting access to credit lines.

The main threat to interpreting the size gradient in drawdowns as causal evidence of loan terms mattering is that large firms may have faced larger cash-flow shocks in the COVID recession. The controls for industry, state, and bond market access already help to alleviate this concern by removing the possibility of large firms operating in more severely impacted industries or states or having used their credit lines solely because of the bond market turmoil in March 2020. To further isolate credit constraints from demand factors, we next explore how the sensitivity of drawdowns to cash-flow shocks varies across the size distribution.

Our main measure of cash-flow shocks is the percent change in national employment in the firm's three digit industry between 2019Q2 and 2020Q2 less the trailing five year change. The abnormal change in industry employment provides an imperfect proxy for the demand shock to a firm, but the measure lines up fairly well with health-related risks and can be calculated for all firms. For example, the five industries with the largest declines in employment all rely heavily on in-person social interactions: scenic and sightseeing transportation, motion picture and sound recording studios, performing arts and spectator sports, clothing stores, and gambling. We report robustness to using the abnormal growth rate of national sales in the firm's three digit industry for the 13 industries included in the Census Retail Sales.

Within firms with more than $1 billion of assets, higher industry exposure strongly predicts higher drawdown rates. The effect of industry exposure on drawdown emerges only in 2020 and indicates that a one standard deviation increase in exposure increases the drawdown rate by roughly 9 percentage points. In contrast, among firms with less than $50 million in assets there is a precisely estimated near zero effect of industry exposure on drawdown rate. We further confirm this pattern in instrumental variable regressions using the physical proximity requirements in an industry as an excluded instrument for the decline in employment. Controlling for maturity and collateral requirements reduces the exposure sensitivity size gradient, providing additional circumstantial evidence that loan terms granting lenders discretion constricted the ability of small firms to borrow.

Finally, we provide evidence that government-provided liquidity can overcome the credit constraints that prevented SMEs from drawing on their credit lines. We match the Y-14 data to a list of participants in the Paycheck Protection Program (PPP) set up under the CARES Act. The PPP provided loans of up to $10 million to to firms with less than 500 employees or satisfying certain other eligibility criteria and further made these loans forgivable if the borrower kept qualifying expenses above specified thresholds. The SMEs in our data that received PPP funds *reduced* their non-PPP bank borrowing in 2020Q2 by an amount equal to 90 percent of their PPP funds.

Related literature. The first contribution of our paper is to document how loan terms vary across the firm size distribution using a newly available supervisory data set with extensive coverage of both SMEs and large firms. In the United States, most of the evidence on loan terms comes from the syndicated loan market, which caters overwhelmingly to large borrowers and loans. Strahan (1999) provides an early and comprehensive analysis of how loan terms vary with size in the syndicated market. He finds that smaller firms in this market have loans with shorter maturity, post more collateral, and pay higher spreads. We show that these patterns become even more pronounced when extending to a sample that includes much smaller firms than appear in the syndicated market. In recent work, Lian and Ma (2020) argue for the primacy of cash-flow over asset-based lending for large firms. We confirm their results but show that for small firms, asset-based lending remains dominant. Berg et al. (2020) provide a more general overview of trends in corporate borrowing of public firms.

Loan-level evidence from non-syndicated loans has mostly relied on special data sets that cover a single segment of the market. Campello et al. (2011) collect survey data on credit line access during the Great Recession for a sample that includes non-syndicated loans but few if any small SMEs. Petersen and Rajan (1994) and Berger and Udell (1995) study a survey of businesses with less than 500 employees with a focus on the effect of relationship strength on the quantity and price of credit. Agarwal et al. (2004) study a proprietary data set from a large financial institution of loan commitments made to 712 privately-held firms. The data sets in these papers mostly contain micro-enterprises that receive loans smaller than the $1 million cutoff for inclusion in the Y14 data. Technologies for lending to microenterprises and small SMEs differ, with the former typically using a score-based algorithm (Berger and Udell, 2006), making it more difficult to compare to large firms. In other countries, credit registries facilitate the analysis of loan terms to SMEs (Jiménez et al., 2009; Ivashina et al., 2020; Crawford et al., 2018; Ioannidou et al., 2019), but bank lending markets differ widely across countries.

The second contribution of our paper is to provide evidence of credit constraints mattering in the COVID recession and to shed light on the role of PPP in alleviating them. In earlier work, Li et al. (2020) documented the sharp increase in bank credit outstanding in 2020Q1 and showed that this increase mostly came from large banks. Acharya and Steffen (2020) show that large firms drew down bank credit lines after the outbreak and raised cash levels. In independent and contemporaneous work, Greenwald et al. (2020) also find that the increase came entirely from credit line drawdowns by large firms. Li et al. (2020) conjectured that these drawdowns reflected large firms drawing on credit lines as a substitute for the bond market disruptions in March (Haddad et al., 2020). Our evidence of substantial drawdowns by firms without bonds outstanding and of the differential response to cash-flow shocks by small and large firms instead emphasizes credit constraints facing small firms as a complementary channel for why only large firms drew liquidity.

More generally, our paper contributes to a debate on whether credit lines actually provide contingent credit when liquidity shocks arrive (Sufi, 2009; Santos and Viswanathan, 2020; Nikolov et al., 2019). Our empirical results show that smaller borrowers were especially vulnerable to being unable to tap their credit commitments following the breakout of COVID-19, in contrast to their use of credit lines in "normal times" (Brown et al., 2020). Due to data limitations, much of this debate has concerned large firms and the role of loan covenants (Roberts and Sufi, 2009; Chodorow-Reich and Falato, 2020; Ippolito et al., 2019; Murfin, 2012). We broaden this focus to include a more general trade-off between commitment and discretion that extends to other loan terms, including maturity and collateral. This is in line with the practical relevance of incomplete contracting and control rights (Hart, 2001), which has lead to an extraordinary rich theory literature on loan terms.[2] Whereas these works consider many applications, we focus on the cross-sectional implications for liquidity provision through credit lines

[2]See for instance Stulz and Johnson (1985); Thakor and Udell (1991); Eisfeldt and Rampini (2009); Rampini and Viswanathan (2010, 2013); Demarzo (2019); Donaldson et al. (2020) on collateral, Flannery (1986); Diamond (1991); Calomiris and Kahn (1991); Diamond (1993); Brunnermeier and Yogo (2009); Brunnermeier and Oehmke (2013); Diamond and He (2014) on maturity, or Smith Jr and Warner (1979); Aghion and Bolton (1992); Berlin and Mester (1992); Garleanu and Zwiebel (2009); Attar et al. (2010); Griffin et al. (2019); Davydenko et al. (2020); Greenwald (2019) on covenants, with some works studying combination of loan terms (Hart and Moore, 1994; Rajan and Winton, 1995; Park, 2000; Donaldson et al., 2019).

(see also Nikolov et al. (2019)). Other works have also studied aggregate liquidity constraints when the banking sector might not be able to honor all credit line draw-downs (Acharya et al., 2018; Greenwald et al., 2020).

The circumstances of the beginning of the COVID recession have additional implications for how to think about credit constraints in bad times across the firm size distribution (Gertler and Gilchrist, 1994). A common view emphasizes shocks to bank health and the cost of setting up new lending relationships as the primary source of credit constraints for small firms (Stiglitz and Weiss, 1981; Petersen and Rajan, 1994; Chodorow-Reich, 2014). We instead provide evidence that small firms could not draw on pre-existing credit lines at a time when the banking sector was flushed with funds. This evidence suggests the importance of looking beyond a simple supply/demand dichotomy and instead to the incomplete nature of financial contracting to understand how bank liquidity flows across the firm size distribution.

2 Data

Our main data source is the FR Y-14Q data collection, which is a supervisory data set maintained by the Federal Reserve to assess capital adequacy and to support stress testing. The FR Y-14Q data contain detailed quarterly data on various asset classes, capital components, and categories of pre-provision net revenue for U.S. bank holding companies, intermediate holding companies of foreign banking organizations, and savings and loan holding companies with more than $100 billion in total consolidated assets.[3]

We use the corporate loan schedule (H.1), which contains loan-level information on loans with a commitment of $1 million or more. We include four types of loans, defined by their line numbers on schedule HC-C of the FR Y-9C reports filed by all bank holding companies: commercial and industrial (C&I) loans to U.S. addresses (Y-9C item 4.a), loans secured by owner-occupied nonfarm nonresidential properties (Y-9C item 1.e(1)), loans to finance agricultural production (Y-9C item 3), and other leases (Y-9C item 10.b). In what follows we parsimoniously refer to these categories all together as 'corporate loans'. For each loan, banks report a large set of characteristics, including the committed amount,

[3]The size cutoff is based on: "(i) the average of the firm's total consolidated assets in the four most recent quarters as reported quarterly on the firm's Consolidated Financial Statements for Holding Companies (FR Y-9C); or (ii) if the firm has not filed an FR Y-9C for each of the most recent four quarters, then the average of the firm's total consolidated assets in the most recent consecutive quarters as reported quarterly on the firm's FR Y-9Cs." Prior to 2020Q2, the respondent panel was comprised of any top-tier BHC or IHC with $50 billion or more in total consolidated assets.

utilized amount, loan type (revolving credit line, term loan, etc.), interest rate, loan purpose, issue date, and maturity date. Further, loans are identified with flags for new loan originations and renewals of existing facilities. Loan renewals encompass minor changes in the terms of the original loan agreement such as re-pricing or maturity extensions. In contrast, a major modification results in a new loan ID and is flagged accordingly. Banks also report whether the loan is secured, and if so, the type of collateral. For a subset of secured facilities that require a constant updating of the collateral market value, banks report the exact value of the underlying collateral or blanket lien. Between 2015Q1 and 2020Q2, around 5.7% of all facilities report the market value of collateral. Existence of and compliance with loan covenants is not reported.

In addition to loan terms, banks report borrower details, including location, industry, internal risk rating, and firm financials. Financials are reported for roughly 60% of borrowers, with reporting positively related to firm size. Financial variables may not be updated quarterly but instead annually or at origination/renewal. Also, banks report whether the financials were audited by an external auditor.

We link borrowers across banks and over time using tax identification numbers . We merge the Y-14 schedule with Compustat via the tax identifier, yielding 4,686 matched firms between 2015Q1 and 2020Q2. Further, we use Compustat-Capital IQ and Mergent FISD to identify firms with access to the bond market.[4] We also merge our data with firms listed as participants in the Paycheck Protection Program (PPP) using a string matching algorithm.

Table 1 reports summary statistics of total commitment by firm size class in 2019Q4, aggregated up to the firm (i.e. borrowing entity) level. Throughout the paper, we split firms into five groups based on assets: less than \$50 million, \$50-249 million, \$250-999 million, \$1-5 billion, and larger than \$5 billion. We will sometimes refer to all firms with less than \$250 million in assets as SMEs[5] and firms with fewer than \$50 million as small SMEs. The assets are as reported in Y-14 and correspond to the assets of the entity that is the primary source of repayment for the facility. We assign each firm to a single size class throughout the sample using the median of the firm's reported asset values over the sample period in 2020Q2 dollars.

Our Y-14 sample, in Panel A, contains 51,248 small SMEs in the data, 11,469 firms with between \$50 and \$250 million in assets, 4,830 firms with between \$250 million and \$1 billion in assets, 3,176 firms

[4]We identify 3,328 firms that either had a bond outstanding according to Compustat-Capital IQ in 2017Q4 or issued a bond at some point from 2010 through 2020 according to Mergent FISD. Of those 3,328 firms, we are able to identify 2,135 in the Y14. Moreover, of the 367 firms that we identify as having issued a bond between March and July 2020 we are able to identify 337 in Y-14.

[5]This matches the assets cutoff used by Ivanov et al. (2020) to define "small private firms" in their analysis of the Y-14 data.

Table 1: *Distribution of Committed Bank Credit by Firm Type and Firm Size.*

Firm Size (Assets in Millions)	Committed Credit (in $mil) 1st Percentile	10th Percentile	Mean	Median	90th Percentile	99th Percentile	Firms in Category
Panel A: All Firms							
Unclassified	1.0	1.1	15.2	2.3	15.1	225.0	24,824
0 – 50	1.0	1.1	5.6	2.6	13.5	37.8	51,248
50 – 250	1.0	1.8	30.6	14.6	74.6	220.5	11,469
250 – 1000	1.0	2.0	99.8	25.6	253.8	938.0	4,830
1000 – 5000	1.0	2.4	300.4	43.9	894.8	2,835.0	3,176
5000–	1.0	2.2	612.4	44.0	1,861.5	6,607.5	2,412
Panel B: Compustat							
0 – 50	1.0	1.0	5.6	2.7	13.3	32.2	1,004
50 – 250	1.0	1.6	41.7	20.0	100.0	333.5	434
250 – 1000	1.0	1.8	134.8	48.9	367.5	1,196.0	707
1000 – 5000	1.0	3.5	436.1	118.3	1,272.9	3,077.1	1,145
5000–	1.2	4.7	981.4	215.5	2,918.0	7,611.8	1,109
Panel C: Syndicated Bank Loans							
0 – 50	1.5	3.7	28.0	11.1	56.1	264.6	202
50 – 250	2.0	7.2	68.7	50.0	133.0	460.6	652
250 – 1000	2.9	11.2	149.7	93.1	375.0	783.6	988
1000 – 5000	4.0	20.6	381.9	224.9	863.8	2,313.3	911
5000–	6.0	78.3	1,071.7	650.1	2,762.3	6,000.0	520

Notes: The table reports the distribution of firm-level committed credit by firm size group. Firm-level commitments are constructed by summing over credits in the Y-14 data. For syndicated credits, the reported participation interest is scaled up to reflect the total commitment and loans held by multiple Y-14 banks are de-duplicated. The sample includes all C&I loans to U.S. addresses, corporate loans secured by owner-occupied nonfarm nonresidential properties, loans to finance agricultural production, and other leases. Panels B and C restrict to firms that appear in Compustat or have syndicated loans, respectively.

with between \$1 and \$5 billion, and 2,412 firms with more than \$5 billion in assets. The table reports total loan commitments to the firm, including syndicated loans held by other lenders.[6] Among small SMEs, the median loan commitment is \$2.6 million, while among firms with more than \$5 billion in assets the median commitment is \$44.0 million. There are also a number of firms missing total asset values that we exclude going forward. Most of these appear to be small firms based on the commitment amount.

Coverage. To ascertain coverage, we first benchmark the Y-14 data to the Y-9C. As of 2019Q4, the Y-9C includes the consolidated balance sheets of all domestic bank holding companies, savings and loan holding companies, U.S intermediate holding companies, and securities holding companies with total assets of at least \$3 billion. In 2019Q4, the Y-9C reported \$4.61 trillion of commitments and \$2.25 trillion of corporate loans outstanding (see Appendix Table A.1). Of these, the largest categories are C&I loans (83% of commitments) and real estate-backed loans (14% of commitments). Our final panel of 29 banks with more than \$100 billion in assets contains \$3.54 trillion of Y-9C commitments, of which \$3.42 trillion are C&I or real estate-backed. The Y-14 schedule at these banks contains \$2.77 trillion of corporate commitments, equal to 60% of total Y-9C lending.

Next, Panels B and C of Table 1 report Y-14 summary statistics for firms in Compustat and with syndicated loans, respectively. The distribution of firms in Compustat tilts to larger firms. Nonetheless, the Y-14 contain 1,004 Compustat firms with less than \$50 million in assets and another 434 firms with between \$50 million and \$250 million in assets, and the distributions of commitment sizes to these firms appear similar to the distributions of commitment sizes to similarly sized firms not in Compustat. However, the analysis that follows cannot be done in Compustat because it involves specific loan terms and drawdown rates. Commonly-used data sets of syndicated loans, such as DealScan or the Shared National Credit Program (SNC), contain some of this information, but tilt even more heavily toward large firms and loans. The Y-14 contains only 202 small SMEs with syndicated loans, which we identify using a syndication field in the Y-14 itself. Even within a firm size class, larger loans have a higher propensity to be syndicated, as reflected in the much higher 10th percentile and median loan sizes in Panel C than in Panel A. These differences highlight the peril of using data on syndicated loans to extrapolate to loan terms for smaller firms.

[6]The total syndicated loan exposure is obtained by scaling up the reported participation interest and then de-duplicating credits held by multiple Y-14 banks.

Representativeness. The Y-14 data are potentially non-representative of the universe of corporate loans along two dimensions. First, they exclude loan commitments of less than $1 million. The Y-14 classifies these loans as small business rather than corporate lending, based on the prevalence of "scored" rather than internally rated lending in the loan decision. Table A.1 shows using Call Report data that C&I and real estate-backed loans of less than $1 million account for less than 10% of total lending in these categories and our analysis will not further account for them.

Second, our sample of lenders excludes small banks that may use a different lending technology (Stein, 2002), although this idea has been disputed (Berger and Udell, 2006). Regardless, table A.1 makes clear that our data include a macroeconomically relevant share of lending to SMEs. We also replicate our key facts in the subset of regional banks in the Y-14 to show that they hold with equal force in both smaller and larger Y-14 respondents (Appendix D) and confirm that loan growth at the start of the COVID recession was *lower* at smaller banks than at Y-14 banks (see also Li et al. (2020)).[7]

3 Illustrative Framework

This section presents an illustrative contracting framework to explain differences in loan terms across firms and draws out the implications for access to liquidity in bad times. We follow the extensive literature on bank lending that makes a distinction between committed and contingent access to credit. Classical models show that committed credit lines can relieve financial constraints by providing *liquidity insurance* (Holmström and Tirole, 1998). However, empirical evidence suggests this insurance view is incomplete: credit lines are contingent and can be revoked or modified following bad news (Sufi, 2009). Lenders in fact often have *discretion* over whether borrowers can access funds. We extend the Holmström and Tirole (1998) framework to capture the trade-off between lender commitment and discretion. We then show that the parameter configurations that lead to discretion also characterize small firms.

3.1 Setup

The firm's problem is a simple version of Holmström and Tirole (1998) with one extension: the firm has uncertain long-term value and can potentially be monitored at the interim stage. Otherwise, assumptions about frictions and timing of cash-flows are standard. Specifically, a firm operates assets of value A.

[7] The regional banks are M&T, Keycorp, Huntington, PNC, Fifth Third, SunTrust, BB&T (now: Truist), US Bancorp, Citizens, Ally, Capital One, and Regions. These banks had average total assets of $253 billion in 2019Q4, compared to average assets of $2.0 trillion at the five largest banks in the Y-14.

There are three periods. At $t = 0$, a penniless firm signs a loan contract with a bank, consisting of a credit limit and loan terms that determine the extent of creditor control. At $t = 1$ a cash-flow shock realizes: per unit of assets, the firm needs to inject additional funds $\rho \sim F = \mathcal{N}(\mu, \sigma^2)$, where $\rho < 0$ has the interpretation of a surprise positive cash-flow shock. Not meeting this obligation implies a dead-weight loss; for simplicity we assume the firm fails and that nothing can be recovered.[8] Finally, at $t = 2$ each unit of assets yields a payoff $z + \epsilon$, where $\epsilon \sim G$ is mean zero and uncorrelated with ρ. The shock ϵ to the firm's terminal value is unknown at date 0 but observable at date 1 if the lender pays a monitoring cost ζ.

The key friction is limited pledgeability: the firm can promise only a share θ of its terminal value to lenders in order to obtain financing. The parameter θ captures the (inverse of) financial frictions and can be micro-founded by moral hazard or cash-flow diversion. The lender is risk-neutral and must break-even on the loan, assuming a discount rate of 0.

The role of credit is to prevent liquidity-driven liquidation at $t = 1$. A firm with credit limit $\hat{\rho}$ can sustain a shock as large as $\hat{\rho}$ and defaults for larger shocks. We assume no new investment opportunities arrive at $t = 0$ that could absorb financing. Incomplete plegeability creates the possibility of credit rationing and inefficient liquidation at date 1: for cash flow shocks ρ between $\theta(z + \epsilon)$ and $z + \epsilon$ the lender loses ex-post even though it would be efficient to keep the firm afloat.

Commitment vs. Discretion The firm chooses between two contractual forms: a committed credit line or a credit line with lender discretion. We model this choice as a dichotomy for simplicity; in practice, the trade-off between commitment and discretion is implemented in a more continuous fashion. The firm chooses the contract that minimizes liquidity-driven default.

Without discretion, the lender commits to a credit limit $\hat{\rho}$ at $t = 0$. The analysis of this case is standard and closely follows Holmström and Tirole (1998). Assuming the pledgeability friction binds, the lender and borrower agree on the largest credit limit that satisfies the lender's participation constraint: $\int_{-\infty}^{\hat{\rho}} \theta z - \rho dF(\rho) = 0$. The normality assumption implies that $\hat{\rho} = \mu + \sigma h^{-1}(\frac{\mu - \theta z}{\sigma})$, where $h(x) = \phi(x)/\Phi(x)$ is the ratio of the standard normal pdf to the standard normal cdf.[9] Importantly,

[8] More generally, lack of funds can lead to costly financial distress, which can take many forms, including downsizing operations or selling assets. While defaults and liquidation are the most extreme forms of financial distress, they are not the most common. The framework is also agnostic on the exact source of the cash-flow shock: it can capture a fall in internal funds or a precautionary motive. Since our focus is on credit line design and use, we do not explicitly model other aspects of corporate liquidity management, such as cash balances, equity issuance, or (dis)investment, that could give rise to a precautionary motive. For fully dynamic models with exogenous contracts, see Bolton et al. (2011) or Nikolov et al. (2019).

[9] Rewrite the participation constraint as $\mathbb{E}[\rho | \rho < \hat{\rho}] = \theta z$ and use the property that the mean of the truncated normal

the credit limit is higher than the expected pledgeable value: $\hat{\rho} > \theta z$. This contract alleviates frictions through an insurance mechanism. Once ρ is realized, the lender would prefer to liquidate the firm if $\rho > \theta z$. However, it is willing to offer a higher credit limit ex-ante because of the existence of good states $\rho < \theta z$; good states cross-subsidize bad states such that the lender breaks even from an ex-ante perspective. This is the *liquidity insurance* view of credit lines. Liquidity insurance requires commitment: ex-post the lender would prefer to revoke the credit line for shocks larger than θz.

In the alternative contractual form, lender discretion introduces the possibility of monitoring before deciding to grant funds at $t = 1$. Discretion relaxes the lender participation constraint by granting an abandonment option whose value increases with uncertainly over terminal value. However, as the logic above makes clear, the pledgeability friction implies that the lender exercises this option inefficiently by denying funds too often. Events at date 1 unfold as follows: (i) the lender observes ρ, i.e. sales are down; (ii) the lender chooses whether to pay cost ξ per unit of assets in order to observe the shock ϵ; (iii) the lender accepts or rejects the request to lend ρ. If the lender rejects, the firm shuts down. Clearly, without monitoring the lending decision can depend only on ρ, while with monitoring it also depends on ϵ. In all cases, the lender chooses the action that maximizes its expected payoff given its information.[10]

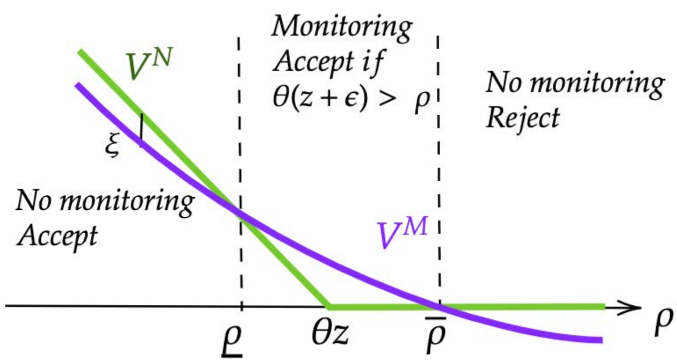
3.2 Equilibrium

We solve for equilibrium in two steps. First, if the contract contains discretion, what is the optimal lender monitoring and rejection strategy? Second, what firm characteristics lead to discretion versus commitment? We focus on the mechanism in the main text and provide a formal derivation in Appendix C.

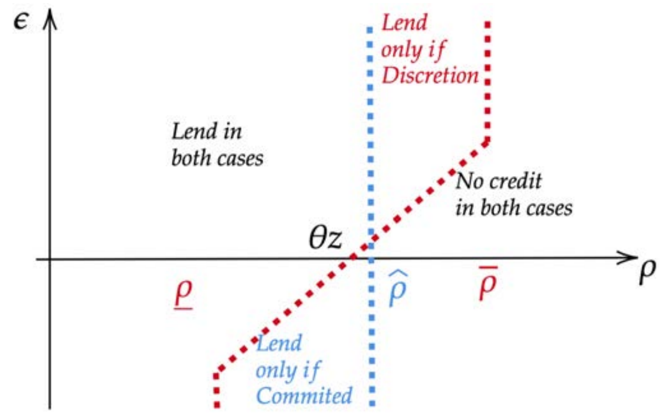
We first show that monitoring only occurs for intermediate values of the date 1 cash-flow shock ρ. Intuitively, small requests for funds are not alarming enough to justify incurring monitoring costs, while large requests are too alarming. Formally, let V^M and V^N denote the expected value to the lender of monitoring and not, respectively. Without monitoring, the lender agrees to lend only when ρ is less than expected pledgeable value θz and its payoff is thus $V^N = \max\{\theta z - \rho, 0\}$. The value of monitoring comes

distribution of $F(\rho)$ over $[-\infty, \hat{\rho}]$ is $\mathbb{E}[\rho|\rho < \hat{\rho}] = \mu - \sigma h\left(\frac{\hat{\rho}-\mu}{\sigma}\right)$.

[10] An alternative theory of monitoring is that it reduces moral hazard. This could take the form of incentivizing the borrower to take costly actions to reduce the likelihood of cash-flow shocks (avoid risk- or illiquidity-shifting). It is well known that giving the lender discretion to withdraw funds after a signal that the borrower has misbehaved can be beneficial (Dewatripont and Tirole, 1994; Acharya et al., 2014; Gorton and Kahn, 2000). While this approach can also rationalize contracts with discretion for small firms if they have worse incentive problems, it seems less applicable to understanding why small firms would receive no funds after a large external shock like the 2020 COVID crisis that is unlikely to be a signal of borrower misbehavior. For that reason, we focus on the case in which cash-flow shocks are exogenous to the borrower.



(a) *Monitoring Region With Discretion*



(b) *Lending Under Discretion Versus Commitment*

Figure 1: *Model Properties*

from avoiding losses by lending only when $\rho < \theta(z+\epsilon)$, and thus $V^M = \mathbb{E}[\max\{\theta(z+\epsilon)-\rho, 0\}] - \xi$. The lender monitors if $V^M > V^N$. The monitoring region is characterized by cutoffs $\underline{\rho}, \overline{\rho}$ such that $V^M > V^N$ if $\rho \in [\underline{\rho}, \overline{\rho}]$. These cutoffs are defined implicitly by $\int_{\theta\epsilon > \underline{\rho}-\theta z} \theta(z+\epsilon) - \underline{\rho} \quad dG(\epsilon) = \theta z - \underline{\rho} + \xi$ and $\int_{\theta\epsilon > \overline{\rho}-\theta z} \theta(z+\epsilon) - \overline{\rho} \quad dG(\epsilon) = \xi$.[11] The left panel of fig. 1 illustrates the monitoring decision graphically.

A first necessary condition for discretion is that the monitoring region be non-empty. Otherwise, the lender never monitors and uses the smallest possible credit limit, equal to θz. In that case, the borrower always prefers commitment to discretion, since the committed limit is $\hat{\rho} > \theta z$. The size of the monitoring range increases in uncertainty over the firm's terminal repayment ability, captured by the variance of ϵ. Intuitively, when uncertainty is low, the *option value of learning* is low. Formally, the variance of ϵ must be large enough relative to the monitoring cost so that $V^M > V^N$ for some realizations of ρ.

With sufficiently large uncertainty over terminal repayment ability, discretion can dominate committed credit. Discretion is more attractive to firms whose pledgeable asset value is both highly uncertain and low relative to the expected $t = 1$ cash-flow shock. The right panel of fig. 1 illustrates lending outcomes under both type of contracts. The figure makes clear the trade-off from choosing discretion — more lending in the high shock region if fundamentals have improved, at the cost of giving up some lending in the low shock region. Therefore, only firms with sufficiently high expected cash-flow shocks and sufficiently high terminal uncertainty prefer discretion. Intuitively, insurance (lender commitment)

[11] The expression defining $\underline{\rho}$ equates the expected net value of monitoring when $\rho < \theta z$ to the expected value of not monitoring. The expected net value of monitoring integrates the cash flows the lender receives $\theta(z+\epsilon) - \underline{\rho}$ over the region where these are positive, and subtracts the monitoring cost ξ. The expected value of not monitoring given $\underline{\rho} < \theta z$ is simply $\theta z - \underline{\rho}$. The expression defining $\overline{\rho}$ is analogous except that when $\rho = \overline{\rho}$ the value of not monitoring is zero.

is less valuable when very large cash-flow shocks are more likely and discretion more valuable when the option value of monitoring is high. Formally, $\mathbb{E}[\rho] > \theta z$ is a second necessary condition for discretion to be chosen.

3.3 Mapping to Firm Size Distribution

Because the cash-flow process is proportional to scale, firm size A plays no direct role.[12] Instead, firms that choose discretion have more ex ante uncertainty over their pledgeable terminal value (greater variance of ϵ) and larger average cash-flow shocks (higher μ) relative to expected pleadgable value (lower z and θ). We provide two types of evidence that link these features to small firms.

First, table 2 uses Y-14 data to show that small firms produce financial statements less frequently and that the financials are less likely to be certified by an external auditor. This evidence expands on earlier work that investigates financial reporting by small firms in much smaller data sets (Allee and Yohn, 2009; Minnis and Sutherland, 2017).[13] The absence of external audits creates further uncertainty over the financial position of a borrower and reduces cash flow pledgeability by increasing the risk of fraudulent accounting.

Second, Appendix table A.3 shows that smaller Compustat firms have higher volatility of revenue, EBITDA, and net income, and that smaller CRSP firms have more volatile stock returns. These results complement recent work documenting that smaller firms are more volatile (Calvino et al., 2018; Herskovic et al., 2020).[14] The intrinsic volatility of small firms also adds to uncertainty about their long-run value.

More generally, associating high uncertainty, high volatility, and low pledgeability with small firms connects to a broader literature which shows that smaller firms tend to be riskier, more opaque, and thus ultimately more constrained (Gertler and Gilchrist, 1994; Petersen and Rajan, 1994; Berger and Udell, 2006; Whited and Wu, 2006; Hennessy and Whited, 2007). This literature has also emphasized

[12]Size would matter directly if monitoring costs did not scale with total assets. On the one hand, a fixed cost of monitoring would imply a cheaper per-unit cost for large firms. On the other, large firms have greater complexity per unit of assets, implying a convex cost of monitoring.

[13]The size gradient in financials and external audit frequency survives inclusion of bank and industry fixed effects and covariates for loan terms (see Table A.2). Gustafson et al. (2020) provide evidence of monitoring in the syndicated market, including site visits and external audits. They find that only about 20% of syndicated loans undergo 'active' monitoring. Plosser and Santos (2016) infer monitoring from changes in internal risk metrics and find that roughly 30% of syndicated credit are adjusted each quarter, and that opaque borrowers are more proactively monitored.

[14]While Compustat and CRSP tilt toward larger firms overall, table 1 shows that these data sets also contain a number of SMEs and that the SMEs in Compustat appear similar to other SMEs in loan size. Small firms not in Compustat likely have other characteristics, such as lower transparency, that would further push in the direction of discretion. Calvino et al. (2018) show that smaller firms have more volatile employment growth using business register data covering 20 countries and that this pattern is not explained by firm age.

Table 2: ***Frequency of Borrower Financials***

	Financials Date			Audit Date			
Assets (mil.)	Ever	Last 2Q	Lag (Qtrs.)	Ever	Last 2Q	Lag (Qtrs.)	Obs.
0-50	.96	.4	3.2	.27	.065	4.8	622257
50-250	.96	.48	2.9	.68	.17	4.3	212128
250-1000	.93	.47	2.9	.82	.25	3.9	146600
1000-5000	.93	.53	2.6	.88	.35	3.4	170367
5000-	.93	.59	2.5	.9	.41	3.1	163265

Notes: The table summarizes the frequency with which the date of financials (or audited financials) are ever reported, whether there is a reported date in the last 2Q, and the average time since the reported date (in quarters) conditional on a date being reported. Sample is 2015Q1-2019Q4. Excludes bank-quarters that rarely report audit dates. Observation count reports the total number of loan-quarters in each size category, regardless of financials reporting.

the relationship aspect of lending to small firms (Petersen and Rajan, 1994; Berger and Udell, 1995; Degryse and Van Cayseele, 2000; Puri et al., 2017). In our framework, relationships exist to facilitate the possibility for information collection and monitoring, as just sharing accounting information at $t = 1$ is unlikely to be credible enough given that these numbers are not easily verifiable nor forward-looking.

3.4 Connection to Loan Terms and Empirical Predictions

A contract with lender discretion can be implemented using loan terms such as demandable or short-maturity debt, collateral, or covenants. Demand loans are analogous to the contract described above — any time the borrower asks for funds, the lender can monitor and reject. Similarly, short-maturity contracts allow the lender to monitor and threaten not to renew if the borrower requests funds. With collateral, the lender can choose to monitor the value of pledged assets and reject if the requested funds exceed this value. Covenants allow the lender to monitor and reject or recall a drawdown if the covenant is violated, although this requires having high quality firm financials updated at quarterly frequency, which may explain why contracts to small firms do not rely solely on covenants.[15] Crucially, all of these terms involve discretion: a lender can roll-over the loan, not mark the collateral to market, and waive a covenant violation. Conversely, commitment is achieved through loan terms agreed upon at $t = 0$, such as a long-term unsecured credit line with weak covenants.

[15]Like most classical models of control rights in financial contracting, the present framework is too stylized to derive the optimal mix of loan terms, i.e. in what instances collateral is better that short maturity. Empirically, the bundling of strict loan terms shown below suggests broad economic forces that transcend any one loan term. Nevertheless, different loan terms give lenders discretion along different dimensions. Collateral requirements or covenants can be used to act on news at high-frequency, but only if the information relates to a specific asset value or financial ratio. Short maturity gives less frequent opportunities to exercise discretion but the renewal decision can be based on any type of information.

We summarize this section with three predictions. First, small firms have loan terms that reflect discretion: short maturity credit lines that must be rolled-over frequently, high collateral requirements, and collateral with uncertain final value such as accounts receivable, inventories, or blanket lien as opposed to fixed assets or real estate.

Second, small firms with contracts that implement discretion may not be able to draw on their credit lines when a cash-flow shock arrives, even if they have funds available "on paper". This evaporation of liquidity is the result of an equilibrium choice: information-sensitive credit limits raise the probability of accessing funds ex-ante, but can restrict small firms ex-post. Through the lens of the model, a shock $\rho > \underline{\rho}$ is not blindly accepted by lenders: if $\rho > \overline{\rho}$ the shock is blindly rejected, while if $\rho \in [\underline{\rho}, \underline{\rho}]$, the shock triggers monitoring and the request for funds is accepted only if fundamentals have improved significantly ($\theta\epsilon > \rho - \theta z$), which likely will not be the case for most small borrowers.[16] We emphasize this is a *relative* prediction; in reality, where discretion versus commitment is more a matter of degree than dichotomy, small firms will be able to draw less than large firms. Moreover, insofar as lender discretion for large firms takes the form of covenants that do not trigger immediately in response to a cash-flow shock, the prediction holds with most force early in a liquidity event.

Finally, the framework has implications for public credit programs aimed at small firms such as PPP. Programs that stimulate credit over and above the market allocation are likely to carry an element of subsidy. The reason is that private contracts are second-best: equilibrium loan terms already maximize the sum of borrower and lender surplus subject to the borrower pledgeability and lender participation constraints. If the public sector faces the same pledgeability frictions, a program that increases credit limits necessarily implies losses on a loan-by-loan basis. Requiring collateral/seniority does not help, since if that could relax pledgeability or participation constraints, private parties would have already incorporated these features.[17] Furthermore, while pledgeability frictions imply that some solvent firms with discretionary contracts do not receive a loan without intervention (those with $\theta(z+\epsilon) < \rho < z+\epsilon$), even in the first-best it is efficient to restrict lending to firms requiring cash flow injections that exceed

[16]It should be clear that monitoring and termination do not necessarily result from the cash-flow shock being unanticipated. Indeed, firms sign contracts with discretion precisely because they expect large cash-flow shocks. News that shifts the distribution of shocks can also trigger renegotiation even before any liquidity need arises. The model implies this would affect the loan agreement at $t = 0$. For example, news of (i) a right-shift of the distribution of cash-flow shocks or (ii) an increase in uncertainty over firms' assets values would make discretion more attractive. Contracts that are newly signed or renegotiated after a COVID-type shock are then more likely to include stricter loan terms.

[17]In fact, the optimal intervention typically mimics private contracts (Tirole, 2012; Philippon and Skreta, 2012; Philippon and Schnabl, 2013). The fiscal consequences of intervention are reduced in two cases. If inefficiencies are rooted in coordination failure or there are large aggregate demand externalities, a "whatever it takes" approach can be effective without imposing much, if any, cost on taxpayers. Second, if the government is a more efficient lender than the banking sector. This is less likely to be the case when banks have strong balance sheets and low cost of funds.

Table 3: ***Maturity at Origination/Renewal by Facility Type and Firm Size Category as of December 31, 2019***

Maturity at Origination/Renewal	Demand	<1 year	1 year	1-2 year	2-4 years	4-5 years	>5 years	Obs.
Assets ($mil.)								
			Panel A: Revolving Credit Lines					
0-50	.29	.23	.23	.16	.058	.028	.013	26924
50-250	.15	.12	.1	.15	.19	.28	.03	8089
250-1000	.076	.046	.04	.066	.17	.56	.045	5924
1000-5000	.024	.021	.021	.033	.15	.71	.047	6598
5000-	.018	.039	.059	.042	.12	.67	.048	6199
			Panel B: Term Loans					
0-50	.0012	.041	.022	.015	.07	.26	.59	13612
50-250	.0013	.04	.022	.024	.14	.43	.34	6222
250-1000	.00061	.032	.014	.034	.13	.48	.31	3293
1000-5000	0	.037	.017	.033	.16	.53	.22	2587
5000-	.0005	.071	.048	.087	.25	.38	.16	1982

Notes: The table reports the fraction of outstanding loans to each firm size group (assets in $million) by the maturity indicated in the table header. The maturity is as of the respective facility's origination date or alternatively the most recent renewal date if the facility has been renewed since origination. The sample includes loans as of December 31, 2019 for which an origination or renewal date is reported.

their long-term value (those with $\rho > z + \epsilon$). Thus, the welfare effects of uniformly increasing credit to small firms are not obvious. Appendix C.2 further studies public credit provision in our framework.

4 Loan Terms Across the Firm Size Distribution

This section documents five facts that show how loan terms create greater lender discretion for small borrowers relative to large borrowers, especially in the provision of credit lines. Appendix D replicates the facts in the subset of regional banks and Appendix E in the subset of public, Compustat-matched borrowers.

Fact 1: Small firms have short-term credit lines, large firms have long-term credit lines. Other loan types have similar maturity across the size distribution. Table 3 reports the distribution of maturity at origination or renewal for all loans outstanding on December 31, 2019, by loan type and firm size.

Panel A restricts to revolving credit lines, the most common loan type and the one most closely tied to liquidity management. Small and large firms differ dramatically in the maturity of their credit lines. For the small SMEs, demand loans, meaning loans immediately callable at the discretion of the lender, constitute 29% of all credit lines. An additional 23% of loans to these SMEs have duration of less than 1 year and another 23% have 364 day credit lines, so that three-quarters of credit lines to small SMEs have 1 year or less of maturity at origination. Less than 10% of credit lines to these firms originate with more than 2 years of maturity.

Credit line maturity rises monotonically and sharply as firm size increases. Half of all credit lines to larger SMEs ($50-250 million in assets) have 2 or more years of maturity at origination and two-thirds of credit lines to these firms have more than 1 year of maturity at origination. For firms with more than $1 billion in assets, less than 10% of credit lines have original maturity of less than 2 years and three-quarters have maturity of greater than 4 years, with the modal credit line a 5 year facility.

Panel B of Table 3 shows that these patterns largely disappear for term loans. For example, less than 20% of term loans to firms of any size class have original maturity of less than 2 years and the majority of term loans have original maturity of greater than 4 years. If anything, small firms have slightly longer maturity term loans at origination. This pattern makes sense through the lens of our theoretical framework, as lenders value discretion most when they have not yet released funds.

Fact 2: All firms actively manage maturity of long-term loans. Small firms do not actively manage maturity of short and medium term loans. Therefore, small firms are more likely to have expiring credit lines. Table 4 pools data over 2015-2020 to explore active maturity management. For each bin of maturity at origination and size class, the table reports the median maturity remaining (in months) just before and after the renewal of a credit agreement.

Credit lines with a maturity at origination of one year or less have almost no active maturity management. The median renewal occurs on a loan with 12 months of maturity at origination and no maturity remaining at the time of renewal; this pattern holds almost uniformly across the firm size distribution. For credit lines with original maturity between one and four years, large firms renew earlier in the loan cycle than small firms. For example, the median renewal on a credit line to a small SME with original maturity of between one and two years occurs one month before expiration, while for a firm with assets above $1 billion the median renewal occurs with one year remaining on the facility. These patterns disappear for the longest maturity credit lines, even reversing, although this maturity category represents less than 5% of credit lines to small SMEs.

The patterns for term loans look similar, with the main difference being that even small SMEs renew medium-term (2-4 years) term loans well in advance of expiration. However, as shown in fact 2, most

Table 4: ***Maturity Management in Revolving Credit Lines and Term Loan by Firm Size Category.***

Assets ($mil.)												
Original Maturity	1 year or less			1-2 years			2-4 years			more than 4		
	Before	After	N	Before	After	N	Before	After	N	Before	After	N
						Panel A: Credit Lines						
0-50	0	12	274076	1	19	73108	6	31	29977	56	61	17679
50-250	0	12	48580	6	21	29236	12	34	38101	38	60	44975
250-1000	0	12	12913	9	22	10501	21	35	34285	36	60	68380
1000-5000	0	12	7626	11	19	7188	26	36	43873	38	60	106056
5000-	1	12	14996	12	20	7116	28	36	36860	44	60	106849
						Panel B: Term Loans						
0-50	0	4	17670	2	18	6975	19	35	30932	47	69	162379
50-250	0	6	8034	6	16	5577	23	33	29441	42	60	95464
250-1000	0	9	3028	12	18	2654	25	33	16214	43	59	50240
1000-5000	1	11	2637	10	20	2142	26	33	14869	45	59	41947
5000-	1	7	5221	12	18	3893	29	34	14902	48	59	27810

Notes: The table reports the median maturity (in months) before and after a credit facility is renewed. Facilities are grouped by their maturity at origination/recent renewal date as noted in the header. Demand loans are excluded from the sample. The sample is restricted to all renewals of revolving credit lines (Panel A) and term loans (Panel B) reported between 2015Q1 through 2019Q4.

Table 5: ***Remaining Maturity by Facility Type and Firm Size Category for Loans Outstanding on December 31, 2019***

Loan Due:	Demand	Jan	Feb	Mar	Q2	Q3-Q4	2021	2022-24	Later	Obs.
Assets ($mil.)										
Panel A: Revolving Credit Lines										
0-50	.28	.029	.029	.032	.19	.27	.1	.055	.0089	37067
50-250	.19	.016	.014	.018	.081	.15	.17	.33	.015	10901
250-1000	.13	.0034	.0038	.0039	.039	.074	.13	.59	.016	8142
1000-5000	.096	.0023	.0026	.0017	.018	.041	.1	.72	.0099	9503
5000-	.078	.0069	.0059	.0068	.022	.053	.092	.72	.014	8662
Panel B: Term Loans										
0-50	.0015	.0043	.0056	.0063	.018	.036	.063	.36	.5	22541
50-250	.0015	.0057	.0058	.0076	.02	.042	.12	.55	.24	8830
250-1000	.0011	.0025	.0034	.0062	.019	.041	.11	.62	.2	4387
1000-5000	0	.0054	.0027	.0072	.019	.04	.097	.68	.14	3333
5000-	.00038	.014	.011	.01	.04	.082	.14	.58	.12	2598

Notes: The table reports the fraction of loans to each firm size group (assets in $milion) with remaining maturity indicated in the table header. The sample includes loans outstanding as of December 31, 2019.

term loans to both small and large firms have more than 4 years of maturity at origination. Across the size distribution, the median renewal on these loans occurs with around 4 years of maturity remaining.

Since the largest firms have primarily long-term credit lines and term loans (fact 1), the evidence in Table 4 confirms the active maturity management for large firms documented in Roberts (2015) and Mian and Santos (2018). At the other extreme, the smallest SMEs overwhelmingly have short-term credit lines that simply get rolled over as they become due. Therefore, while large firms rarely have expiring credit, small firms frequently do. Table 5 shows this outcome explicitly by reporting the distribution of maturity remaining as of December 31, 2019, by loan type and firm size. Less than 3% of term loans to firms in any size class came due in 2020Q1 and 70% or more of term loans outstanding at the end of 2019 did not mature until 2022 or later. Similarly, only 15% of credit lines to the largest firms had maturity remaining of less than one year and the modal loan had maturity remaining of around three years, consistent with evidence from the syndicated loan market documented in Chodorow-Reich and Falato (2020). In sharp contrast, nearly 40% of loans to the smallest SMEs were immediately callable or due in the first quarter of 2020 and 85% were due sometime in 2020.

Together, facts 1 and 2 describe one way that lenders maintain discretion over pre-committed credit to small firms: they lend at short maturity which requires more frequent rollover decisions. More

Table 6: ***Collateral Use by Facility Type and Firm Size Category as of December 31, 2019***

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets ($mil.)								
Panel A1: Revolving Credit Lines (Non-Demand Loans)								
0-50	.023	.015	.47	.029	.049	.38	.037	26762
50-250	.025	.026	.44	.057	.083	.28	.092	8792
250-1000	.015	.043	.37	.048	.11	.25	.17	7073
1000-5000	.0054	.038	.31	.039	.11	.18	.32	8586
5000-	.0019	.018	.1	.015	.074	.074	.71	7987
Panel A2: Revolving Credit Lines (Demand Loans)								
0-50	.0077	.012	.66	.034	.049	.16	.079	10942
50-250	.0055	.026	.37	.084	.037	.11	.37	2901
250-1000	.0017	.02	.18	.069	.018	.058	.65	1773
1000-5000	.0007	.022	.11	.0056	.012	.046	.81	1423
5000-	0	.015	.053	.0041	.02	.026	.88	984
Panel B: Term Loans								
0-50	.48	.0044	.11	.12	.025	.25	.019	22508
50-250	.24	.012	.13	.31	.043	.23	.026	8817
250-1000	.14	.027	.13	.35	.056	.24	.063	4382
1000-5000	.074	.028	.14	.18	.086	.23	.26	3333
5000-	.02	.018	.082	.23	.068	.15	.44	2597

Notes: The table reports the fraction of loan commitments to each firm size group (by assets in $million) with the type of collateral indicated in the table header. The sample includes loans as of December 31, 2019.

frequent rollover decisions for small firms in turn give the lender greater opportunity to adjust loan terms or withdraw credit.

Fact 3: Small firms almost always post collateral while large firms often borrow unsecured. Table 6 reports the distribution of loans by firm size and the main type of collateral posted, if any, as of the end of 2019. The Y-14 groups collateral types into real estate, fixed assets, accounts receivable & inventory (AR&I for short), cash, other specified assets, blanket lien, and unsecured. These collateral types differ in the protection they provide to a lender and the frequency of revaluation. Real estate and fixed assets are illiquid claims with stable valuations. AR&I are more liquid claims whose value can move at arbitrarily high frequency depending on the reporting requirements imposed by the lender, causing the effective loan limit to fluctuate as well. Blanket liens give a lender priority over unsecured lenders in bankruptcy but do not otherwise provide a specific claim.

As shown in Panel A1 and in line with facts documented in Luck and Santos (2020), less than 10% of non-demand revolving credit lines to SMEs are unsecured. Within those that are collateralized, half are backed by AR&I, with blanket liens accounting for most of the remainder. The share unsecured rises to 17% for revolving credit lines to firms with assets between $250 million and $1 billion, 32% for loans to firms with assets between $1 and $5 billion, and 71% for loans to firms in the largest size class. A similar gradient holds among demand loans (Panel A2), with less than 10% of demand loans to the smallest firms unsecured and 88% of demand loans to the largest firms unsecured. Again, AR&I are the dominant source of collateral.

Differences in collateral requirements are equally stark for term loans, shown in Panel B. Only 2% of term loans to firms with less than $50 million of assets are unsecured. The share unsecured rises monotonically with firm size to 26% for loans to firms with assets between $1 and $5 billion and 44% for the largest firms. In contrast to credit lines, real estate is the typical security for term loans to small borrowers and fixed assets the typical security for larger firms.

Appendix table A.4 documents differences in collateral posting across industries; for example, firms in the retail sector have a higher propensity to post AR&I, reflecting their need for working capital and their large inventories. However, these differences do not explain the size gradient in collateral, as we confirm in regressions that control for industry reported in table A.5 in the Appendix.

In sum, small firms also provide lenders with discretion on pre-committed lines of credit by posting collateral that lenders can re-value at high frequency.

Fact 4: In normal times, small firms have higher, more volatile utilization of credit lines. Table 7 shows the utilization rate on credit lines at the end of 2019. Nearly one-third of small SMEs had utilization rates above 70%, compared to only 6% of the largest firms. Conversely, three-quarters of the largest firms had utilization rates below 10%, compared to one-third of small SMEs. The final column shows that small SMEs also exhibit more variation in credit utilization in normal times, measured as a larger average absolute quarterly change over 2015-2019. Together, the high mean level and unconditional volatility of utilization at small firms reflect their reliance on credit lines as a source of financing in normal times (see also Brown et al., 2020; Greenwald et al., 2020), in sharp contrast to the evidence from the COVID period below. This evidence is also in line with smaller firms having larger cash-flow shocks than large firms, as discussed in the illustrative framework above.

Taken together, the high average utilization (fact 3) and reliance of small firms on collateralized

Table 7: ***Drawdown of Revolving Credit Lines by Firm Size, 2019Q4***

	Utilization/Commitment							
Assets (mil.)	$< 10\%$	10– 30%	30– 50%	50– 70%	70– 90%	$> 90\%$	$\lvert\Delta$ Util./ Comm. % $\rvert$	Obs.
0-50	.33	.087	.12	.15	.14	.17	10	36827
50-250	.35	.1	.12	.15	.14	.14	9.4	10928
250-1000	.37	.12	.14	.15	.12	.094	8.4	8122
1000-5000	.47	.16	.13	.11	.075	.067	7.7	9447
>5000	.77	.08	.053	.03	.014	.056	4.5	8729

Notes: The table reports the distribution of drawn credit as share of total commitments and the average change in the absolute value of drawn credit as a share of total commitments. The distribution is reported for 2019Q4. Changes in drawn credit are based on the period 2015Q1 through 2019Q4. Observations report the number of loans in each size category in 2019Q4.

credit facilities (fact 2) suggest small firms' access to liquidity is more sensitive to the collateral values. We investigate this more directly in the Internet Appendix using the market value of collateral, which is reported for roughly 6% of loan quarters, and a multivariate regression (see Figure A.1). Indeed, we find that the sensitivity of utilization to collateral values is: i) roughly twice as large for small SMEs as large firms; ii) greatest for facilities backed by AR&I and (albeit noisily) real estate; iii) higher for facilities that are closer to their collateral constraint. Hence, collateral constraints result in greater variation in liquidity over time, particularly for small firms with more binding terms.

Finally, existing work has suggested that firms with less undrawn credit have incentives to hold cash instead (Sufi, 2009; Lins et al., 2010; Acharya et al., 2014; Berg, 2018; Nikolov et al., 2019). Table A.6 in the Appendix confirms that smaller firms have higher cash-to-assets ratios. In the next section, we will control for initial cash holdings when investigating cross-sectional differences in drawdown rates during the COVID-19 recession.

Fact 5: Small firms pay higher spreads, even conditional on observable firm and bank characteristics. Earlier facts document that smaller firms have shorter maturity credit lines, less active maturity management, and post more collateral than larger firms. Our final fact shows that small firms do not receive the benefit of lower spreads in exchange for these stricter loan terms. We refer to this arrangement as small firms choosing loan terms from a different menu rather than choosing different items from the same menu as large firms.

Table 8 reports the distribution of interest rates on loans outstanding at the end of 2019, by firm size and loan type. For both credit lines and term loans, the interest rate distribution for the smallest firms

Table 8: ***Interest Rates by Facility Type and Firm Size Category on December 31, 2019***

Interest in bp	0 -100	100-200	200-300	300-400	400 -500	500 -600	>600	Obs.
Assets ($mil.)								
				Panel A: Revolving Credit Lines				
0-50	.015	.01	.054	.3	.41	.17	.04	24293
50-250	.048	.03	.16	.4	.2	.076	.083	7392
250-1000	.068	.026	.16	.34	.22	.091	.1	5489
1000-5000	.086	.017	.21	.37	.16	.078	.075	5817
5000-	.2	.02	.24	.32	.11	.053	.053	2623
				Panel B: Term Loans				
0-50	.015	.0018	.029	.38	.42	.13	.026	22541
50-250	.024	.0031	.074	.49	.28	.079	.054	8826
250-1000	.026	.0059	.11	.47	.24	.076	.07	4386
1000-5000	.035	.011	.2	.54	.13	.045	.036	3333
5000-	.094	.019	.26	.46	.12	.029	.013	2598

Notes: The table reports the fraction of loan commitments to each firm size group (by assets in $million) with the interest rate indicated in the table header. Interest rates represent the reference rate plus spread for floating rate loans and fixed interest rate for fixed rate loans, both as of December 31, 2019. Interest rates for revolving credit lines are only reported if the drawdown is strictly larger than zero. The sample includes loans as of December 31, 2019.

first order stochastically dominates the distribution for the second smallest size class, and so on up to the largest firms who face the lowest spreads.

Observable characteristics of the borrower and lender only partially explain these differences. Table 9 reports regressions of the interest rate on size class and reference-rate$\times$time fixed effects, with loans to the smallest SMEs the omitted category. Thus, the coefficients have the interpretation of the additional spread, in basis points, for firms in each size class relative to the smallest SMEs. For both credit lines (column 1) and term loans (column 5), the unconditional differences in spreads are economically large; the mean spread on a loan to a firm with more than $5 billion in assets is more than 100 basis points lower than to a small SME. Columns (2) and (6) add industry, lender and rating fixed effects as well as firm financial characteristics — debt/assets, cash and receivables/assets, operating income/interest expense, and net income/assets — where the fixed effects and the financial variables are allowed to vary over time by interacting with time fixed effect. Including all of these observable firm characteristics reduces the size gradient for both credit lines and term loans by roughly one-third relative to the specification with no controls, but a substantial difference of around 80 basis points remains. This persistent difference suggests small borrowers are risky beyond observable characteristics, consistent with concerns about unverifiable financial statements or other soft information known to the lender.

Table 9: ***Pricing of Revolving Credit Lines and Term Loans by Firm Size Category***.

Dependent variable	Interest Rate (in bp)						
Sample	Credit Lines				Term Loans		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
50-250 (in mil)	-62.0***	-36.3***	-35.6***	-35.7***	-17.4***	-12.2***	-11.2***
	(2.1)	(1.7)	(1.7)	(1.7)	(2.3)	(1.8)	(1.8)
250-1000	-55.6***	-37.0***	-35.7***	-35.6***	-13.0**	-8.7**	-5.5
	(3.7)	(2.9)	(3.2)	(3.2)	(4.1)	(3.0)	(3.0)
1000-5000	-69.2***	-63.0***	-58.5***	-58.2***	-66.5***	-53.1***	-39.7***
	(3.2)	(2.7)	(3.3)	(3.3)	(3.7)	(3.1)	(3.3)
5000-	-113.9***	-85.3***	-76.2***	-76.0***	-107.3***	-79.7***	-63.4***
	(4.1)	(4.5)	(5.1)	(5.1)	(4.0)	(3.6)	(3.8)
Reference-Rate-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Bank-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Rating-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Firm Financial Controls	No	Yes	Yes	Yes	No	Yes	Yes
Loan Terms Controls	No	No	Yes	Yes	No	No	Yes
Drawdown	No	No	No	Yes	No	No	Yes
No of Firms	41645	37172	37053	37053	31208	26314	26214
N	130277	114102	112545	112545	61320	53822	52412
R^2	0.359	0.553	0.566	0.566	0.279	0.521	0.535

Notes: Results from estimating a model of the following type: $\text{Interest}_{\ell,t} = \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \mathbb{I}\{\text{size class} = s\} + \Gamma' X_t + \epsilon_{\ell,t}$ where $\text{Interest}_{\ell,i,b,t}$ is the interest on facility ℓ from bank b to firm i at time t. The sample contains originations and renewals between 2015Q1 and 2019Q4. Industry×time fixed effects are at the NAICS 3-digit level. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are lagged debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense. Loan term controls are six maturity categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years), six collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), and total credit line commitment over total assets. Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Columns (3) and (7) additionally control for maturity- and collateral-time fixed effects and loan commitment size/assets. These additional loan terms further reduce the size gradient. Interpreting this evidence requires care, because loan terms and interest rates are jointly determined. Since small firms have stricter terms — shorter maturity and higher collateral requirements — the fact that controlling for these terms *reduces* the credit line gradient indicates that these other terms must also reflect additional information about credit worthiness or market power not encoded in the rating or firm financials. Put differently, the reduction in the pricing gradient implies there is an omitted variable, like borrower quality, that is positively correlated with size and maturity and negatively correlated with collateral and interest rates, as suggested by our theory. Finally, Column (4) shows that differences in utilization of credit lines across small and large firms (fact 4) do not add any additional explanatory power.[18] Finally

[18]The large gradient in term loans also helps to rule out differences in drawdown rates as well as in fees specific to either credit lines or term loans (Berg et al., 2016), which we do not observe.

Table A.7 in the Appendix shows that market concentration cannot explain the size gradient, alleviating the concern that it only reflects differences in market power (Wang et al., 2020).

5 COVID and Drawdowns

We now assess how these differences in loan terms influenced firms' access to liquidity in the first half of 2020. First we describe unconditional differences in credit line utilization, then we estimate drawdown rates controlling for firm characteristics, next we present evidence of heterogeneous utilization in response to the COVID shock, and finally we discuss the interaction with the PPP.

5.1 Drawdowns by Firm Size

Table 10 displays the change in reported bank credit by size class and loan type in 2019Q4, 2020Q1, and 2020Q2. The Y-14 does not include loans made under the Paycheck Protection Program (PPP), so these totals exclude any PPP credit in 2020Q2. The percent change in bank credit outstanding during the COVID period increases monotonically in the firm size distribution. SMEs experienced essentially no change in credit in 2020Q1 and a contraction in 2020Q2. In contrast, firms with assets above $1 billion as a group had an increase in credit of 44% in 2020Q1. Thus, only large firms accessed bank liquidity in 2020Q1. The absence of any increase in debt at small firms and the overall size gradient are also apparent in total firm debt rather than just Y-14 credit. Appendix Table A.8 replicates the table using a balanced panel of firms with balance sheet data reported in both 2019Q4 and 2020Q1, ruling out the possibility that unobserved debts explain these patterns.

The evolution of credit outstanding overwhelmingly reflects differential drawdown rates on existing credit line facilities, as shown in the right-most panel of table 10. In other words, the extensive margins of rollover and new loans did not "bark" at the start of the recession, although the threat of non rollover may have constrained small firms from drawing on existing lines. The lower panel makes clear that the large drawdowns cannot be fully explained by bond market disruptions in March 2020, as drawdowns occurred even at firms that have never accessed the bond market and commercial paper backup facilities account for a small portion of overall activity.

To account for covariates more formally, we estimate loan-level difference-in-difference regressions of the utilization rate on credit lines by firm size and an indicator for 2020Q1 or 2020Q2. We focus on drawdown rates on existing credit lines because Table 10 showed that almost all of the increase in bank

Table 10: *Aggregate Drawdowns in $B by Firm Type, 2019Q4-2020Q2*

	Total Y-14 Credit			Term Loans			CL Drawdowns (all facilities)			CL Drawdowns (pre-existing facilities)		
	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2
Panel A: By Firm Size (in Assets in $mil)												
Not classified	138.0	141.5	141.1	58.7	60.5	62.4	48.2	51.5	46.2	44.4	48.0	39.4
0-50	186.3	188.6	159.7	67.5	67.7	67.1	102.4	104.4	73.5	99.7	102.0	70.9
50-250	187.1	193.8	169.0	62.2	62.5	59.4	102.2	108.9	86.0	100.8	106.9	83.6
250-1000	185.2	212.7	186.5	56.9	57.2	53.1	105.8	133.1	109.6	103.4	131.4	107.3
1000-5000	238.6	317.6	266.5	77.4	82.2	77.9	125.3	199.0	151.4	124.1	197.8	149.0
5000-	240.2	373.4	300.1	97.9	118.2	113.3	73.6	184.6	115.2	72.2	182.7	111.8
Sum	1175.3	1427.6	1222.8	420.6	448.3	433.1	557.5	781.5	581.9	544.7	768.6	562.0
Panel B: Other Firm Characteristics												
Bond Market Access	332.9	503.7	407.0	125.2	146.4	139.3	129.6	277.1	185.5	127.6	275.0	181.5
Bond Issued March-July	95.5	169.2	124.4	36.8	45.2	39.5	28.0	92.6	54.8	27.7	92.2	54.3
CP Facilities	3.2	10.1	5.4	1.1	1.7	1.6	1.8	8.1	3.2	1.8	8.1	3.0

Notes: The table reports the total dollar amount (in $billions) of utilized credit pooling all facilities (left-most columns), term loans (second set of columns), revolving credit lines only (third set of columns), and revolving credit lines of firms that had a facility open as of the previous quarter (right-most columns). The columns headered "Total Y-14 Credit" include non-revolving credit lines, capitalized lease obligations, and other unclassified loan types in addition to term loans and credit line drawdowns. In Panel B, we restrict the sample to firms that have bond market access (the firm either had a bond outstanding according to Compustat-Capital IQ in 2017Q4 or issued a bond at some point from 2010 through 2020 according to Mergent FISD.), firms that issued a bond in March-July 2020, and loans that have the purpose to back up a Commercial Paper (CP) facility.

credit occurred on these lines (see also Greenwald et al., 2020). The basic specification takes the form:

$$\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_s \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID} \right] + \epsilon_{\ell,t}, \quad (1)$$

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit and COVID is an indicator for 2020Q1 or 2020Q2. All specifications include time and loan fixed effects. Thus, the coefficients on the interaction terms have the interpretation of the average additional drawdown in 2020 for firms in the indicated size class relative to small SMEs. We cluster standard errors by three-digit NAICS industry.

Table 11 reports results. In column (1), drawdown rates rise monotonically in firm size, with the largest size class exhibiting an incremental 14 percentage point drawdown rate in 2020. The difference in drawdown rates between small SMEs and every other size class is highly statistically significant, as is the difference between drawdowns at the largest firms and large SMEs. Column (2) adds an indicator for whether the firm has issued bonds, interacted with COVID, to capture potential differences in loan demand arising from the bond market disruptions in March 2020. The coefficient on this term indicates a small (1.8 p.p.) additional drawdown among firms in the bond market over and above the size gradient. Including it only modestly reduces the size gradient, indicating that disruptions in the bond market by themselves cannot explain the differences between large and small firms, consistent with many bond issuers leaving their credit line untouched in 2020Q1 (Darmouni and Siani, 2020).

Column (3) replaces the time fixed effects with bank-time fixed effects to absorb differences in loan supply across banks. Columns (4) and (5) add state-time and three- digit industry-time fixed effects, respectively, to absorb aspects of loan demand associated with these dimensions. Collectively, these fixed effects reduce the size gradient to a statistically significant 8.2 p.p. difference between small SMEs and large firms. Column (6) adds controls for two measures of leverage commonly used in covenants, debt/assets and operating income/interest expense, a measure of profitability, net income/assets, cash over assets, and categorical variables for the internal firm rating, each interacted with COVID. These controls slightly *increase* the size gradient to 9.3 p.p., echoing our finding in fact 5 that observable firm characteristics cannot explain the pricing gradient by firm size. It also indicates that SMEs' larger cash holdings do not explain their lower drawdown rates.

Column (7) explores the potential scope for loan terms to explain the differential in drawdowns. The regression includes controls for collateral type and maturity bin, as well as their interactions with the COVID indicator. Including loan controls reduces the size gradient by about 40%. Furthermore, the

Table 11: ***Drawdowns by Firm Size.***

Dependent variable	Drawdown Rate (in ppt)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
50-250 (in mil) × COVID	4.1***	4.0***	3.0***	3.0***	2.2***	2.1***	0.5	0.7**
	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.4)	(0.3)
250-1000 × COVID	10.5***	10.3***	8.8***	8.6***	6.7***	6.9***	3.9***	4.0***
	(1.2)	(1.2)	(1.0)	(1.0)	(1.1)	(1.1)	(0.9)	(0.6)
1000-5000 × COVID	13.5***	12.6***	10.8***	10.6***	8.8***	9.2***	5.4***	6.0***
	(1.7)	(1.6)	(1.1)	(1.1)	(1.0)	(1.0)	(1.0)	(0.8)
5000- × COVID	14.1***	12.6***	10.2***	9.9***	8.2***	9.3***	5.3***	5.0***
	(2.4)	(2.1)	(1.5)	(1.5)	(1.4)	(1.4)	(1.4)	(1.2)
Bond Market × COVID		1.8*	1.6	1.6*	1.3	1.3*	0.9	0.5
		(1.0)	(1.0)	(0.9)	(0.8)	(0.8)	(0.8)	(0.8)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No	No	No
Bank-Time FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	No	No	No	Yes	Yes	Yes	Yes
Financials	No	No	No	No	No	Yes	Yes	Yes
Rating-Time FE	No	No	No	No	No	Yes	Yes	Yes
Maturity Controls	No	No	No	No	No	No	Yes	Yes
Collateral Controls	No	No	No	No	No	No	Yes	Yes
Interest Rate Controls	No	No	No	No	No	No	No	Yes
Drawdown in 2019q4	No	No	No	No	No	No	No	Yes
No of Firms	62615	62615	62615	62615	62614	60196	60195	43654
N	786188	786188	786188	786186	786156	756619	756540	549043
R^2	.83	.83	.83	.83	.83	.83	.83	.83

Notes: Results from estimating a model of the following type: $\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_{s,1} \left[\mathbb{I}\{\text{size class} = s\}\right] \times \text{COVID} + \Gamma' \times X_\ell \times \text{COVID} + \epsilon_{\ell,t}$ where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit and COVID is an indicator for 2020Q1 and 2020Q2. We restrict the sample to outstanding loans from 2017Q4 onwards. Bond Market_i indicates whether firm i has issued bonds at any point between 2010 and 2020Q2. Industry×time fixed effects are at the NAICS 3 digit level. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are lagged debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense, each interacted with COVID. Maturity and collateral controls are six maturity categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years) and six collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), each interacted with COVID. Robust standard errors are clustered at the three digit NAICS level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

coefficients on the loan term controls, reported in Table A.9, are consistent with loan terms mattering. Drawdown rates increase with maturity, while loans backed by accounts receivable and inventory (AR&I) have lower drawdown rates than credit lines backed by blanket liens or unsecured, both consistent with a role for the additional discretion these terms afford lenders. Delving a step further, the maturity gradient is steeper for unsecured or blanket lien lines, as shown in Figure A.2. For SMEs, drawdown activity is roughly 10pp higher for loans due after 2022 relative to loans due in 2020, whereas for loans secured by specific assets, such as cash, AR&I, real estate or fixed assets, the difference is only 5pp, consistent with a complemenatry role for collateral in restricting drawdowns especially for longer maturity loans. A similar pattern holds for larger firms, but with wider confidence intervals due to the small number of large firms with short-maturity, secured loans.

Finally, Table 11 column (8) additionally controls for the interest rate and the 2019Q4 utilization rate bin, each interacted with COVID.[19] The spread control absorbs differences in drawdowns resulting from different pricing and has a *positive* coefficient. The ex ante drawdown controls for mechanical effects of being close to the loan limit. The size gradient remains essentially unchanged with these controls. Even small SMEs with unused capacity did not draw.[20] Taken together, our analysis shows that SMEs faced less access to liquidity in response to the COVID recessions and that the difference appears at least partly explained by more restrictive maturity and collateral terms.[21]

5.2 Drawdowns by Firm Size and Industry Exposure

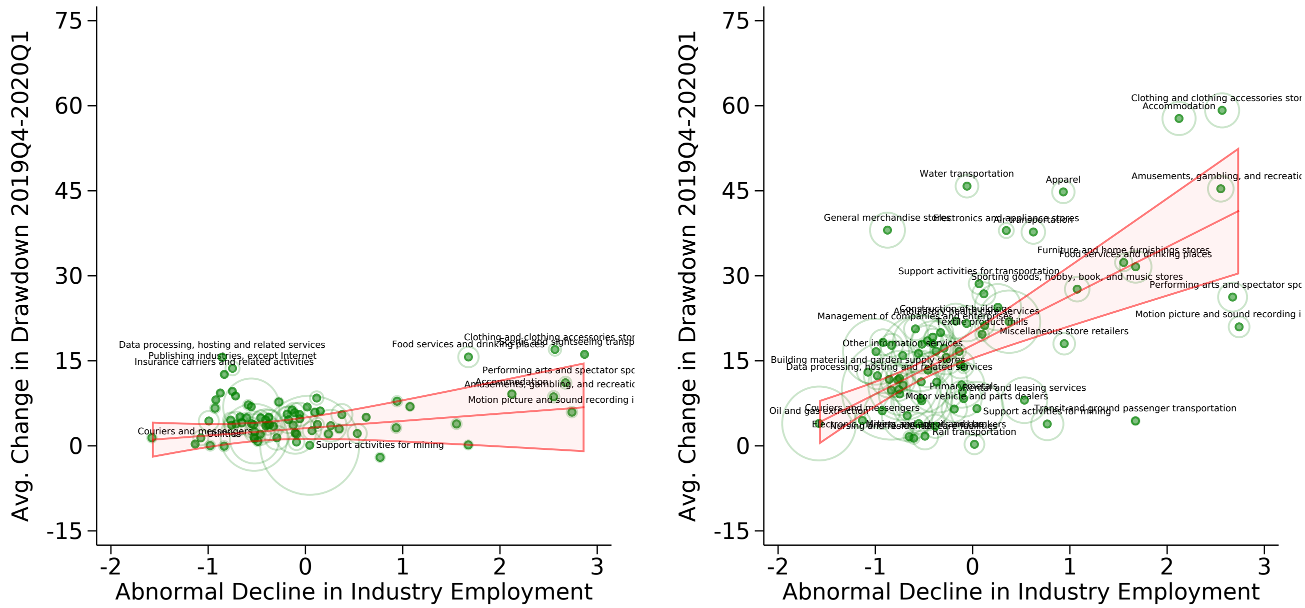
The main threat to interpreting the size gradient in drawdowns as causal evidence of loan terms mattering is that large firms may have faced larger cash-flow shocks in the COVID recession. The controls for industry, state, and bond market access in Table 11 already help to alleviate this concern by removing the possibility of large firms operating in more severely impacted industries or states or having used their credit lines solely because of the bond market turmoil in March 2020. To further isolate credit constraints from demand factors, we now show that the sensitivity of drawdowns to cash-flow shocks varies across the size distribution.

We construct two measures of cash-flow shocks. Our main measure uses the percent change in national employment in the firm's three digit industry between 2019Q2 and 2020Q2 using data from the Bureau of Labor Statistics Current Employment Statistics. The change in employment provides an imperfect proxy for the demand shock to a firm, but as we will see shortly the measure lines up well with health-related risks and can be calculated for all firms. We report robustness to using the percent change in national sales between 2019Q2 and 2020Q2 in the firm's three digit industry, a measure that more closely accords with the theoretical notion of a cash-flow shock but is available only for 13 industries included in the Census Retail Sales. For both measures, we detrend by subtracting from the 2019Q2-2020Q2 change the average Q2-to-Q2 growth rate between 2015 and 2019 and refer to the

[19]Including these variables shrinks the sample somewhat since computing the spread requires a non-zero drawdown in 2019Q4. We have verified that the sample change alone has almost no impact on the coefficients.

[20]Table A.10 reports the distribution of utilization rates in 2020Q1 and 2020Q2. Comparing to table 7, the fraction of small SMEs with utilization below 10% fell by only 3 percentage points between 2019Q4 and 2020Q1. In contrast, the fraction of firms with more than $5 billion in assets with utilization below 10% fell by 25 percentage points from 2019Q4 to 2020Q1. These differences echo the result in column (8) that the drawdowns in 2020Q1 do not simply reflect which firms had unused capacity on their credit lines on paper, as even small SMEs with unused capacity did not draw.

[21]One caveat is that we lack valid instruments for loan terms which are endogenously determined in conjunction with each other. Nevertheless, our findings are consistent with the equilibrium outcomes summarized in the model.



(a) *SMEs (Assets<$250 million)*

(b) *Large Firms (Assets>$1 billion)*

Figure 2: ***Exposure to COVID-shock and Credit Line Drawdowns for SMEs and Large Firms.*** *Abnormal employment decline is the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. We add linear fits with industries weighted by number of firms per industry. Data restricted to industries with at least 10 firms per firm size category. Perimeter of hollow circles indicate relative industry size by number of firms reporting in the Y14 within the respective size class.*

resulting measure as the abnormal employment or sales change.[22]

Figure 2 plots the industry average change in drawdown between 2019Q4 and 2020Q1 against the industry abnormal decline in employment, separately for SMEs (left panel) and firms with more than $1 billion in assets (right panel). Appendix fig. A.3 reports the corresponding plots for each of our five size categories. Employment exposure successfully identifies industries likely to suffer in a recession caused by risks of disease contagion; the industries with the highest exposure are scenic and sightseeing transportation, motion picture and sound recording studios, performing arts and spectator sports, clothing stores, gambling, accommodation, restaurants, and ground passenger transportation. Yet, SMEs in these industries draw on their credit lines at a similar rate as SMEs in less affected industries. In contrast, the right panel shows that firms with more than $1 billion in assets in highly exposed industries have drawdown rates economically and statistically much higher than firms in less exposed industries. Thus, cash-flow shocks translated into credit line drawdowns at large but not at small firms.

We confirm this pattern in loan-level difference-in-difference and triple-difference regressions

[22]The detrending has almost no practical impact because the variation during COVID far exceeds the variation in pre-COVID trends. The correlation between the raw and detrended change is 0.986 for the employment measure and 0.992 for the retail sales measure.

Table 12: ***Drawdowns by Firm Size and Exposure to COVID-19 shock: Abnormal 3-digit Industry Decline in Employment***

Dependent variable	Drawdown Rate (in ppt)					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × COVID	3.1	-0.4	0.8	0.9	0.9	-0.2
	(2.3)	(2.2)	(1.4)	(1.3)	(1.2)	(2.0)
Exposure × 50-250 (in mil) × COVID		3.5***	2.4***	2.2***	2.2***	1.3*
		(1.3)	(0.8)	(0.8)	(0.7)	(0.8)
Exposure × 250-1000 × COVID		4.4**	3.3**	3.3**	3.3**	2.0
		(2.1)	(1.6)	(1.4)	(1.3)	(1.4)
Exposure × 1000-5000 × COVID		7.2***	6.1***	6.1***	5.9***	3.9***
		(2.2)	(1.7)	(1.5)	(1.4)	(1.3)
Exposure × 5000- × COVID		9.5***	8.2***	8.2***	7.7***	4.6*
		(3.2)	(2.8)	(2.7)	(2.6)	(2.4)
50-250 (in mil) × COVID		4.6***	3.3***	3.3***	3.3***	1.1***
		(0.5)	(0.6)	(0.6)	(0.6)	(0.3)
250-1000 × COVID		11.3***	9.5***	9.2***	9.4***	4.8***
		(1.2)	(1.0)	(0.9)	(1.0)	(0.8)
1000-5000 × COVID		15.4***	13.2***	12.9***	12.5***	7.5***
		(1.7)	(1.1)	(1.0)	(1.0)	(0.8)
5000- × COVID		18.0***	15.1***	14.7***	14.4***	7.5***
		(2.6)	(1.9)	(1.9)	(1.9)	(1.6)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No
Bank-Time FE	No	No	Yes	Yes	Yes	Yes
State-Time FE	No	No	No	Yes	Yes	Yes
Financials	No	No	No	No	Yes	Yes
Rating-Time FE	No	No	No	No	Yes	Yes
Loan Terms	No	No	No	No	No	Yes
No of Firms	60117	60117	60117	60117	57781	41860
N	756529	756529	756529	756527	727947	527452
R^2	0.83	0.83	0.83	0.83	0.83	0.83

Notes: Results from estimating a model of the following type: $\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \sum_{s\neq\{\$0-50m\}} \beta_{1,s} \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \beta_2 \left[\text{Exposure}_i \times \text{COVID}\right] + \sum_{s\neq\{\$0-50m\}} \beta_{3,s} \left[\text{Exposure} \times \mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \epsilon_{\ell,i,t}$. where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2 and Exposure_i is the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. We restrict the sample to outstanding loans from 2017Q4 onwards. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are lagged debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense, each interacted with COVID. Loan term controls are six maturity categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years), six collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), 5 categories of drawdown prior to COVID (<20%, 20-40%, 40-60%, 60-80%, and >80%), and interest rate spreads, each in levels and interacted with COVID.Robust standard errors are clustered at the 3-digit NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

summarized in Table 12. Column (1) gives the difference-in-difference effect of higher industry exposure on drawdowns in 2020Q1, using the employment exposure measure. In this table we standardize exposure to have unit variance, so the coefficient has the interpretation that one standard deviation higher industry exposure results in a 3.4 percentage point higher drawdown rate in 2020Q1.

Column (2) reports the triple-difference specification:

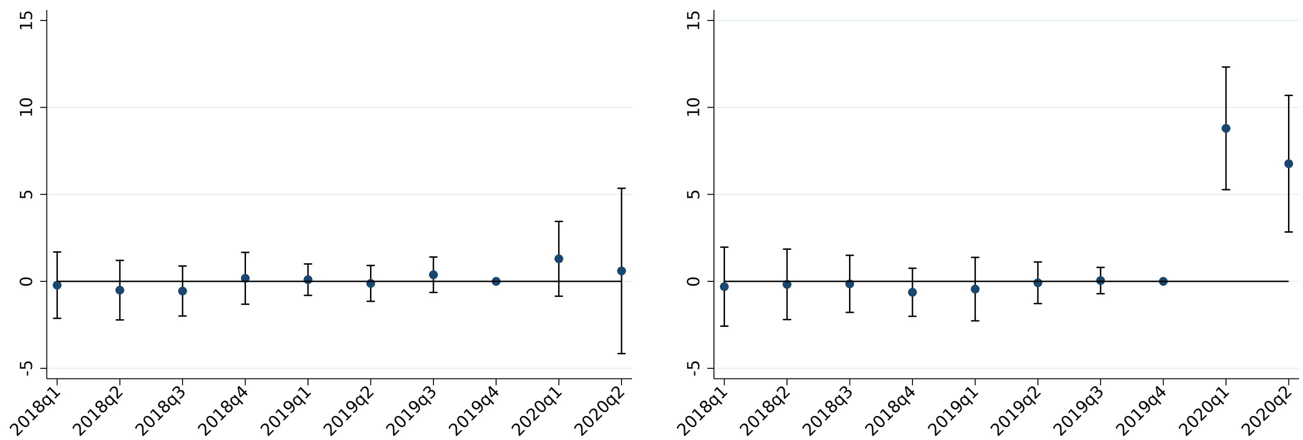
$$\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \beta_2 \left[\text{Exposure}_i \times \text{COVID}\right]$$
$$+ \sum_{s \neq \{\$0-50m\}} \beta_{3,s} \left[\text{Exposure} \times \mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \epsilon_{\ell,i,t}. \tag{2}$$

One standard deviation higher exposure has essentially no impact on the drawdown rate at small SMEs and the data do not reject a marginal impact of zero. The marginal impact of higher exposure rises monotonically in the firm-size distribution, up to a sensitivity of 9 percentage points per standard deviation of exposure for firms with more than $5 billion of assets. The standard errors reject equality of the coefficients in the largest and smallest size class categories at the 1% level.

Figure 3 traces out the quarter-by-quarter dynamic responses to the specification in column (2) for two size classes, SMEs and firms with more than $1 billion in assets. Appendix fig. A.4 reports the corresponding plots for each of our five size categories. For each size class, the figure reports the quarterly coefficients from estimating the specification in column (2) among firms in that size class and interacting Exposure with each calendar quarter. There is no evidence of pre-trends, meaning that firms in industries experiencing a larger employment decline during the COVID recession did not have either rising or declining drawdowns in previous quarters. For SMEs, higher exposure has a small impact on drawdowns in 2020Q1 and 2020Q2. For large firms, the impact of Exposure jumps in 2020Q1 and falls slightly in 2020Q2.

Returning to table 12, columns (3) to (5) show robustness to including additional covariates. Column (3) replaces time fixed effects with bank-time fixed effects to control for differences in credit supply across banks. The triple interaction coefficients fall slightly but a large and statistically significant size gradient remains. Column (4) adds state-time fixed effects with little further impact. Column (5) adds controls for firm financials, rating, and bond market access each interacted with COVID, again with little impact.

Column (6) adds interactions of loan terms — maturity, collateral, spread, and 2019Q4 utilization — with Exposure and COVID. Figure A.4 in the Appendix reports the coefficients on these additional terms and shows they generally have the same sign as in table 11, with the marginal impact of Exposure on drawdown increasing with maturity and decreasing with collateral. Including these controls also reduces the size gradient in the impact of Exposure, again suggesting that restrictive loan terms inhibited the ability of firms — especially small firms — to access pre-committed credit.



(a) *<$250 million*

(b) *>$1 billion*

Figure 3: ***Dyamics of Credit Line Drawdowns for SMEs and Large Firms during the COVID Recession.*** *The figure plots the sequence of coefficients $\{\beta_t\}$ obtained from estimating $Drawdown_{\ell,t} = \alpha_\ell + \delta_t + \beta_t \times Exposure_i + \epsilon_{\ell,i,t}$, where $Drawdown_{\ell,t}$ is the ratio of utilized to committed credit and $Exposure_i$ is the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. Coefficients are normalized to 2019Q4 and 95% confidence bands.*

Appendix Table A.11 repeats the analysis for the retail sales exposure measure. We obtain very similar results, with exposure mattering more to larger firms. The magnitude of the gradient is similar to the employment exposure measure but the difference loses statistical significance for the largest firms simply because the sample of firms in retail or restaurants contains many fewer very large firms.

To further rule out confounding shocks that operate at the industry level, table 13 reports instrumental variable regressions that treat the employment change in 2020 as an endogenous variable. The excluded instrument is the physical proximity requirements in the industry. Specifically, we start with the ONET survey question "How physically close to other people are you when you perform your current job?" and average the occupation-level responses within each industry using employment shares as weights.[23] To ease interpretation, we report a cross-sectional specification with the dependent variable the change in the loan's drawdown rate between 2019Q4 and 2020Q1.

The first two columns pool size classes and compare the OLS and IV coefficients. The instrument is strong, with an effective F-statistic of 17.5.[24] The IV coefficient is smaller than the OLS coefficient but estimated with less precision and the data do not reject equality. The next several columns report the IV

[23]This is question 21 in the work context module (https://www.onetcenter.org/dl_files/MS_Word/Work_Context.pdf). Azzimonti et al. (2020) also use this ONET question to measure exposure to COVID. The employment shares come from the 2018 Occupational Employment Statistics (https://www.bls.gov/oes/).

[24]Montiel Olea and Pflueger (2013) introduce the effective F-statistic as the proper metric of first stage strength with non-iid standard errors. See Andrews et al. (2019) for further discussion. Alternatively, collapsing the data to the three digit industry level (unweighted), the first stage regression of employment change on this measure has an F-statistic of 20.9.

Table 13: ***Instrumenting Industry Exposure with Physical Proximity Needs.***

Dependent variable	Δ Drawdown$_{2020Q1-2019Q4}$ (in ppt)						
Estimation	OLS	2SLS					
Firm Size	All		<\$50	\$50-\$250	\$250-\$1000	\$1000-\$5000	>\$5000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	3.9***	2.6	-0.8	0.9	4.2*	7.3***	12.8***
	(1.4)	(2.4)	(2.4)	(2.9)	(2.5)	(2.1)	(4.8)
F-Statistic (MP)	.	17.475	16.912	16.891	14.247	15.684	9.745
No of Firms	43806	43806	29184	7195	3488	2403	1536
N	67081	67081	33040	9812	7452	8732	8045

Notes: This table shows results from estimating a model of the following type: $\Delta\text{Drawdown}_{i2020Q1-2019Q4} = \text{Exposure}_i + \epsilon_{it}$, where $\Delta\text{Drawdown}_{i2020Q1-2019Q4}$ is the difference in firm i's and Exposure$_i$ is the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. In column (2) through (7), we instrument Exposure$_i$ with the responses to the ONET survey question "How physically close to other people are you when you perform your current job?" aggregated to the industry-level. Effective F-statistic reported according to Montiel Olea and Pflueger (2013). Standard errors are clustered by 3-digit NAICS code.

coefficient separately by firm size class. Consistent with the results in table 12, higher industry exposure has essentially no impact on drawdowns for the smallest firms and a monotonically increasing impact in the size distribution, up to a marginal impact of a standard deviation of exposure of 13 percentage points for the largest firms.

Finally, while the lag in and infrequency of financials reporting in the Y-14 makes it difficult to ascribe the motivation for drawdowns, survey evidence offers some clues. The Federal Reserve Senior Loan Officer Survey asks a panel of large banks about whether and why loan demand changed. In April, the most common responses were precautionary demand for liquidity (100% of banks experiencing an increase in loan demand described it as very important) and a decline in internal funds (74%). In contrast, relatively few respondents (28%) cited declines in other sources of financing and none cited increased real investment. An increased precautionary motive, reflective of the unprecedented uncertainty at the end of March about the course of the pandemic, and decline in internal funds, presumably due to the wave of business shutdowns, both evoke the cash-flow shock modeled in section 3.

5.3 Bank Balance Sheets versus Economic Environment

Banks could have forced credit reductions on borrowers in 2020Q1 because of changes in the economic outlook or in their own balance sheet capacity. In either case, these reductions would concentrate on firms with loan terms that grant banks some discretion, namely, small firms. Nonetheless, distinguishing between bank constraints and the outlook for firms matters centrally to policy questions such as whether direct support to banks would pass through to small firms.

A variety of evidence suggests that changes in the economic environment better explain the constriction of credit to small firms in 2020Q1. Already, a number of our specifications include bank×time fixed effects, which rule out differences in balance sheet capacity across banks in explaining the size gradient in credit drawdowns. Using bank balance lending data, Li et al. (2020) show that pre-crisis financial conditions did not constrain large banks' liquidity supply. Table A.12 confirms their results in our loan-level data and shows that differences in capital, liquid assets or deposits across banks cannot explain away the size gradient in drawdowns in 2020Q1. The Federal Reserve Senior Loan Officer Survey also asks about whether and why banks tightened lending standards. According to the April 2020 Survey, while 60% of large banks tightened lending standards, less than 10 percent of respondents said it was due to a deterioration in their current/expected capital or liquidity position. Instead, the vast majority of banks cited a less favorable economic outlook or worsening of industry-specific problems as very important reasons for tightening credit. Figure A.5 in the Appendix corroborates the survey results by showing that loan-level default probabilities reported in the Y-14 rose in 2020. Importantly, default probabilities rose across the firm size distribution, consistent with the interaction of a deteriorating economic situation and ex ante discretion in loan terms to small firms explaining why only small firms did not draw.

This discussion highlights the importance of looking beyond a simple supply/demand dichotomy in the presence of contingent contracts. It is common in empirical work in banking to trace differences in credit to either "demand" shocks (differential need for funds across firms) or "supply" shocks (typically, a reduction in bank lending capacity). We have just argued that neither credit demand nor bank lending capacity can fully account for the differences in credit across the firm size distribution in 2020. Instead, we take the view that credit lines, as opposed to simple goods, are incomplete contracts whose terms dictate allocation of control rights in different contingencies. This incomplete contracting view explains the differences in credit across the firm size distribution in 2020, even in the absence of clear differential demand shocks or any large impairments in banks' balance sheets.

In sum, unlike the 2008 crisis that originated in capital and liquidity shortfalls on bank balance sheets,[25] the 2020 credit crunch to small firms appears to primarily reflect weaknesses in the outlook for borrowers due to the recession and the discretion in loan terms to small firms. In that case, policy support for liquidity to small firms requires direct subsidies, as we turn to next.

[25] See among others Ivashina and Scharfstein (2010); Acharya and Mora (2015); Chodorow-Reich and Falato (2020); Ippolito et al. (2019).

Table 14: *Aggregate Drawdowns for PPP Participants by Firm Size, 2019Q4-2020Q2*

	Non-PPP Credit Outstanding ($Bil)			PPP Amount	Repayment	
Firm assets ($mil)	2019Q4	2020Q1	2020Q2	($Bil)	Ratio (%)	N
Not classified	11.4	11.5	10.8	3.6	19.5	6857
0-50	101.6	103.0	79.5	32.8	71.7	38508
50-250	68.9	69.7	57.1	11.5	109.0	5055
250-1000	22.0	23.7	20.4	1.6	201.2	935
1000-5000	11.2	16.6	12.3	0.3	1431.3	248
5000-	7.8	12.5	9.6	0.1	2268.8	110
Sum	222.7	237.0	189.7	50.0	94.7	51713

Notes: The table reports the total dollar amount (in $B) of non-PPP credit outstanding (left-most three columns), total PPP funds received, and the ratio of the change in credit outstanding between 2020Q1 and 2020Q2 to PPP funds received for the PPP recipients identified in the Y-14.

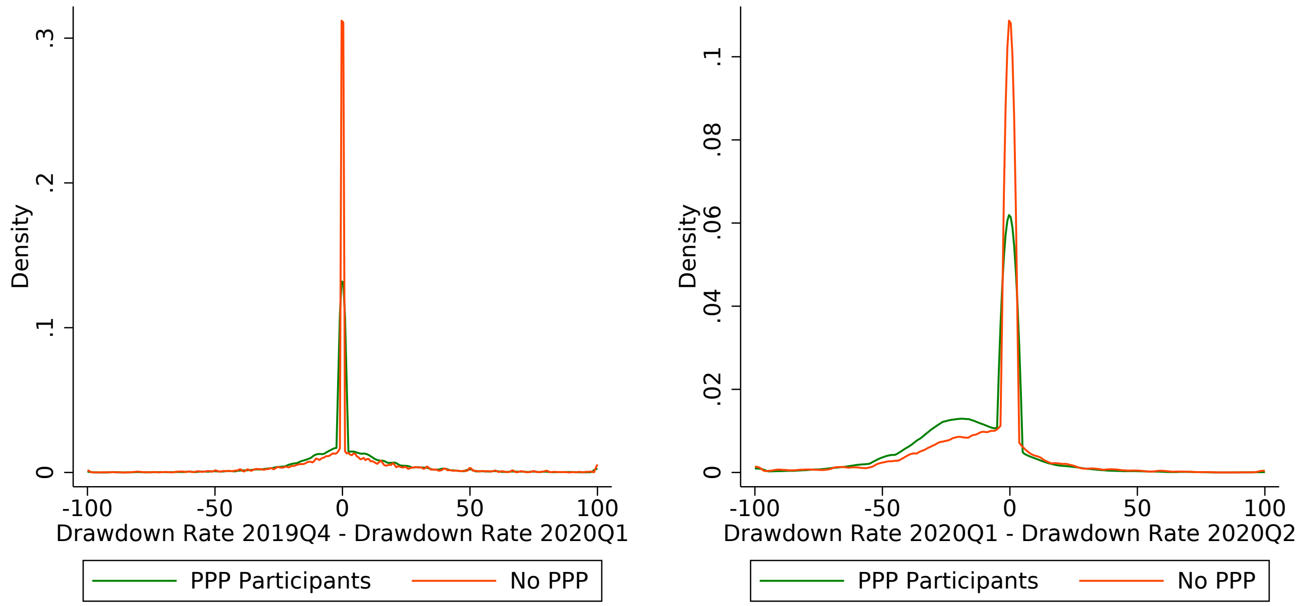
5.4 Paycheck Protection Program

The Paycheck Protection Program (PPP) was established in the CARES Act and signed into law on March 27, 2020, with the first loans signed on April 3, 2020. The program offered term loans of an amount equal to 2.5 months payroll (capped at $10 million) with minimum maturity of 2 (later increased to 5) years and a maximum interest rate of 4% (later set to 1%) to firms with less than 500 employees or satisfying certain other eligibility criteria. In addition, firms that maintained expenses over an 8 week period (later extended to 24 weeks) covering payroll costs, interest on mortgages, rent, and utilities in excess of the loan amount, and where payroll costs absorbed at least 75% of the loan amount (later lowered to 60%), could have the loan forgiven. More than 5 million borrowers received PPP loans. In response to a Freedom of Information request, the Small Business Administration made available a file containing the names, addresses, and loan amounts of all PPP recipients. We "hand" match this file to the Y-14 data using the borrower's name and address.

Table 14 reports the non-PPP loan balances for the firms we can identify as PPP recipients as well as the PPP amount. We identify 51,713 current Y-14 borrowers as PPP recipients. Consistent with the eligibility rules for program participation, 97% of the PPP loans to Y-14 borrowers with non-missing assets go to SMEs, with the vast majority going to small SMEs.

SMEs that took PPP loans had no net increase in their credit line utilization in 2020Q1, similar to other SMEs.[26] However, these firms account for a disproportionately large share of loan repayments in

[26] In Appendix table A.13 we project PPP take-up on several firm and loan characterstics. Firms that obtained PPP loans were in more exposed industries (based on our employment exposure measure), had shorter maturity credit lines, and were more likely to have posted AR&I collateral. Li and Strahan (2020) highlight the role of banking relationships in accessing PPP funds.



(a) *Drawdown Rate Change from 2019Q4 to 20120Q1* **(b)** *Drawdown Rate Change from 2020Q1 to 2020Q2*

Figure 4: *Kernel Density of Drawdowns at Small SMEs*

2020Q2. Total credit outstanding to small SMEs fell by $28.9 billion in 2020Q2 (see table 10). Borrowers we match to the PPP file contribute 81% of this decline, despite accounting for only 54% of the 2020Q1 outstanding. This likely understates the overall contribution of PPP firms, since there may be "type-II" errors of firms we fail to match because of spelling errors or other abnormalities. A similar pattern holds for large SMEs.

Figure 4 shows that PPP recipients were more likely than other firms to repay non-PPP credit in 2020Q2. The figure displays kernel density plots of the change in utilized credit at small SMEs, separately by PPP receipt. The densities for 2020Q1 in the left panel appear indistinguishable. In contrast, the right panel clearly shows a higher repayment propensity at PPP recipients.

We can calculate the ratio of aggregate non-PPP bank debt repayments to PPP disbursements among Y-14 PPP recipients. For small SME recipients, debt repayments equal 72% of the PPP disbursement. The ratio exceeds 100% for large SMEs, and pooling across all firms non-PPP credit fell by an amount equal to 95% of the PPP disbursement. While the smaller pass-through to debt repayment among small SMEs is consistent with their having more unmet liquidity needs pre-PPP, the high absolute pass-through may seem surprising. One explanation is that the precautionary demand for cash in 2020Q1 subsided somewhat in 2020Q2 as overall uncertainty lessened. In any case, these results indicate that the government-sponsored provision of PPP funds substantially if not totally counteracted the credit constraints that prevented eligible SMEs from drawing down private credit lines in 2020Q1.[27]

6 Conclusion

Smaller borrowers sign loan contracts with stricter terms that leave substantial discretion to the lender in providing funds. As a result, bank liquidity in bad times flows toward larger borrowers.

Our evidence does not show that small firms never access bank liquidity, nor that large firms always can. In fact, using the same regulatory dataset, Brown et al. (2020) find that small firms extensively draw on their credit lines to weather idiosyncratic cash-flow shocks in "normal" times. A literature analyzing covenant violations by large firms finds that their credit lines are not fully committed either (Sufi, 2009). These patterns reveal the complex economics behind bank liquidity provision to firms and that the tightness of financial constraints varies with the size and nature of the shock. Nevertheless, it is clear that credit available "on paper" in good times can severely overstate what firms can actually access in bad times, and especially so for small firms.

We have laid out a set of facts and patterns to encourage future work toward a unifying theory of loan terms. While our simple framework emphasizes a choice between *commitment* and *discretion* which rationalizes cross-sectional differences in access to bank liquidity, there are a number of other forces that could enrich the analysis. These include how different loan terms best target specific frictions or borrower types, the role of borrower misbehavior and incentive constraints, and the possibility of creditor conflict when drawdowns from one bank may be used to repay another. We have not featured these last two forces because our analysis of the COVID episode mostly concerns the consequences of a large external shock to small borrowers, most of whom have one or two bank creditors. In other circumstances, they would prove more important.

It would also be fruitful to study the implications of these frictions on firm dynamics and industrial organization. Large firms not only enjoy better access to liquidity insurance, they also can more easily substitute to nonbank sources of liquidity. Hence, small firms are more likely to face costly options to manage their liquidity in bad times, including reduced investment, self insurance, downsizing, or exit. We leave these questions to further research.

[27] Consistent with a substantial part of PPP being used to strengthen firms' balance sheets, Granja et al. (2020) and Chetty et al. (2020) provide evidence that the program did not have an immediate impact on payrolls. Bartlett and Morse (2020) find a positive impact of PPP but only at smaller firms than are in our data.

References

Acharya, V., H. Almeida, F. Ippolito, and A. Perez (2014). Credit lines as monitored liquidity insurance: Theory and evidence. *Journal of Financial Economics 112*(3), 287 – 319.

Acharya, V. V., H. Almeida, F. Ippolito, and A. Perez-Orive (2018). Credit lines and the liquidity insurance channel. *Available at SSRN 2795794*.

Acharya, V. V. and N. Mora (2015). A crisis of banks as liquidity providers. *The Journal of Finance 70*(1), 1–43.

Acharya, V. V. and S. Steffen (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of covid. *Review of Corporate Finance Studies, forthcoming*.

Agarwal, S., S. Chomsisengphet, and J. C. Driscoll (2004). Loan commitments and private firms. *Economic Perspective*.

Aghion, P. and P. Bolton (1992). An incomplete contracts approach to financial contracting. *The review of economic Studies 59*(3), 473–494.

Allee, K. D. and T. L. Yohn (2009). The demand for financial statements in an unregulated environment: An examination of the production and use of financial statements by privately held small businesses. *The Accounting Review 84*(1), 1–25.

Andrews, I., J. Stock, and L. Sun (2019). Weak instruments in iv regression: Theory and practice. *Annual Review of Economics 11*.

Attar, A., C. Casamatta, A. Chassagnon, and J.-P. Décamps (2010). Multiple lenders, strategic default and the role of debt covenants.

Azzimonti, M., A. Fogli, F. Perri, and M. Ponder (2020, August). Pandemic control in econ-epi networks. Working Paper 27741, National Bureau of Economic Research.

Bartlett, R. and A. Morse (2020). Small business survival capabilities and policy effectiveness: Evidence from oakland.

Berg, T. (2018). Got rejected? real effects of not getting a loan. *The Review of Financial Studies 31*(12), 4912–4957.

Berg, T., A. Saunders, and S. Steffen (2016). The total cost of corporate borrowing in the loan market: Don't ignore the fees. *The Journal of Finance 71*(3), 1357–1392.

Berg, T., A. Saunders, and S. Steffen (2020). Trends in corporate borrowing. *Annual Review of Financial Economics*.

Berger, A. N. and G. F. Udell (1995). Relationship lending and lines of credit in small firm finance. *Journal of business*, 351–381.

Berger, A. N. and G. F. Udell (2006). A more complete conceptual framework for sme finance. *Journal of Banking & Finance 30*(11), 2945–2966.

Berlin, M. and L. J. Mester (1992). Debt covenants and renegotiation. *Journal of Financial Intermediation 2*(2), 95–133.

Bolton, P., H. Chen, and N. Wang (2011). A unified theory of tobin's q, corporate investment, financing, and risk management. *The journal of finance 66*(5), 1545–1578.

Brown, J. R., M. Gustafson, and I. Ivanov (2020). Weathering cash flow shocks. *The Journal of Finance*.

Brunnermeier, M. K. and M. Oehmke (2013). The maturity rat race. *The Journal of Finance 68*(2), 483–521.

Brunnermeier, M. K. and M. Yogo (2009). A note on liquidity risk management. *American Economic Review 99*(2), 578–83.

Calomiris, C. W. and C. M. Kahn (1991). The role of demandable debt in structuring optimal banking arrangements. *The American Economic Review*, 497–513.

Calvino, F., C. Criscuolo, C. Menon, and A. Secchi (2018). Growth volatility and size: A firm-level study. *Journal of Economic Dynamics and Control 90*, 390 – 407.

Campello, M., E. Giambona, J. R. Graham, and C. R. Harvey (2011, 04). Liquidity Management and Corporate Investment During a Financial Crisis. *The Review of Financial Studies 24*(6), 1944–1979.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, and T. O. I. Team (2020, June). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data. Working Paper 27431, National Bureau of Economic Research.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008-9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Chodorow-Reich, G. and A. Falato (2020). The loan covenant channel: How bank health transmits to nonfinancial firms.

Crawford, G. S., N. Pavanini, and F. Schivardi (2018). Asymmetric information and imperfect competition in lending markets. *American Economic Review 108*(7), 1659–1701.

Darmouni, O. and K. Siani (2020). Crowding out bank loans: Liquidity-driven bond issuance. *Available at SSRN 3693282*.

Davydenko, S. A., R. Elkamhi, and M. Salerno (2020). When are financial covenants relevant? *Available at SSRN 3554454*.

Degryse, H. and P. Van Cayseele (2000). Relationship lending within a bank-based system: Evidence from european small business data. *Journal of financial Intermediation 9*(1), 90–109.

Demarzo, P. M. (2019). Presidential address: Collateral and commitment. *The Journal of Finance 74*(4), 1587–1619.

Dewatripont, M. and J. Tirole (1994). A theory of debt and equity: Diversity of securities and manager-shareholder congruence. *The quarterly journal of economics 109*(4), 1027–1054.

Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *the Quarterly Journal of economics 106*(3), 709–737.

Diamond, D. W. (1993). Seniority and maturity of debt contracts. *Journal of financial Economics 33*(3), 341–368.

Diamond, D. W. and Z. He (2014). A theory of debt maturity: the long and short of debt overhang. *The Journal of Finance 69*(2), 719–762.

Donaldson, J., D. Gromb, and G. Piacentino (2019). Conflicting priorities: A theory of covenants and collateral. Technical report.

Donaldson, J. R., D. Gromb, and G. Piacentino (2020). The paradox of pledgeability. *Journal of Financial Economics 137*(3), 591–605.

Eisfeldt, A. L. and A. A. Rampini (2009). Leasing, ability to repossess, and debt capacity. *The Review of Financial Studies 22*(4), 1621–1657.

Flannery, M. J. (1986). Asymmetric information and risky debt maturity choice. *The Journal of Finance 41*(1), 19–37.

Garleanu, N. and J. Zwiebel (2009). Design and renegotiation of debt covenants. *The Review of Financial Studies 22*(2), 749–781.

Gatev, E. and P. E. Strahan (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The Journal of Finance 61*(2), 867–892.

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

Gorton, G. and J. Kahn (2000). The design of bank loan contracts. *The Review of Financial Studies 13*(2), 331–364.

Granja, J., C. Makridis, C. Yannelis, and E. Zwick (2020, May). Did the paycheck protection program hit the target? Working Paper 27095, National Bureau of Economic Research.

Greenwald, D. (2019). Firm debt covenants and the macroeconomy: The interest coverage channel. *Manuscript, July*.

Greenwald, D., J. Krainer, and P. Paul (2020). The credit line channel.

Griffin, T. P., G. Nini, and D. C. Smith (2019). Losing control? the 20-year decline in loan covenant restrictions.

Gustafson, M., I. Ivanov, and R. R. Meisenzahl (2020). Bank monitoring: Evidence from syndicated loans. *Available at SSRN 2831455*.

Haddad, V., A. Moreira, and T. Muir (2020). When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fed's response.

Hart, O. (2001). Financial contracting. *Journal of economic Literature 39*(4), 1079–1100.

Hart, O. and J. Moore (1994). A theory of debt based on the inalienability of human capital. *The Quarterly Journal of Economics 109*(4), 841–879.

Hennessy, C. A. and T. M. Whited (2007). How costly is external financing? evidence from a structural estimation. *The Journal of Finance 62*(4), 1705–1745.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuwerburgh (2020). Firm volatility in granular networks. *Journal of Political Economy 128*(11), 4097–4162.

Holmström, B. and J. Tirole (1998). Private and public supply of liquidity. *Journal of political Economy 106*(1), 1–40.

Ioannidou, V., N. Pavanini, and Y. Peng (2019). Collateral and asymmetric information in lending markets.

Ippolito, F., H. Almeida, A. P. Orive, and V. Acharya (2019). Bank lines of credit as contingent liquidity: Covenant violations and their implications. *Journal of Financial Intermediation*, 100817.

Ivanov, I., L. Pettit, and T. M. Whited (2020). Taxes depress corporate borrowing: Evidence from private firms. *Available at SSRN 3694869*.

Ivashina, V., L. Laeven, and E. Moral-Benito (2020). Loan types and the bank lending channel. Technical report, National Bureau of Economic Research.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial economics 97*(3), 319–338.

Jiménez, G., J. A. Lopez, and J. Saurina (2009, 08). Empirical Analysis of Corporate Credit Lines. *The Review of Financial Studies 22*(12), 5069–5098.

Kashyap, A. K., R. Rajan, and J. C. Stein (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of finance 57*(1), 33–73.

Li, L., P. Strahan, and S. Zhang (2020, May). Banks as lenders of first resort: Evidence from the covid-19 crisis. Working Paper 27256, National Bureau of Economic Research.

Li, L. and P. E. Strahan (2020). Who supplies ppp loans (and does it matter)? banks, relationships and the covid crisis. *Banks, Relationships and the COVID Crisis (October 13, 2020)*.

Lian, C. and Y. Ma (2020). Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics*.

Lins, K. V., H. Servaes, and P. Tufano (2010). What drives corporate liquidity? an international survey of cash holdings and lines of credit. *Journal of financial economics 98*(1), 160–176.

Luck, S. and J. A. C. Santos (2020). The valuation of collateral in bank lending. *Available at SSRN 3467316*.

Mian, A. and J. Santos (2018). Liquidity risk and maturity management over the credit cycle. *Journal of Financial Economics 127*(2), 264–284.

Minnis, M. and A. Sutherland (2017). Financial statements as monitoring mechanisms: Evidence from small commercial loans. *Journal of Accounting Research 55*(1), 197–233.

Montiel Olea, J. and C. Pflueger (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics 31*(3), 358–369.

Murfin, J. (2012). The supply-side determinants of loan contract strictness. *The Journal of Finance 67*(5), 1565–1601.

Nikolov, B., L. Schmid, and R. Steri (2019). Dynamic corporate liquidity. *Journal of Financial Economics 132*(1), 76–102.

Park, C. (2000). Monitoring and structure of debt contracts. *The Journal of Finance 55*(5), 2157–2195.

Petersen, M. A. and R. G. Rajan (1994). The benefits of lending relationships: Evidence from small business data. *The journal of finance 49*(1), 3–37.

Philippon, T. and P. Schnabl (2013). Efficient recapitalization. *The Journal of Finance 68*(1), 1–42.

Philippon, T. and V. Skreta (2012). Optimal interventions in markets with adverse selection. *American Economic Review 102*(1), 1–28.

Plosser, M. and J. Santos (2016). Bank monitoring. *Available at SSRN 2697146*.

Puri, M., J. Rocholl, and S. Steffen (2017). What do a million observations have to say about loan defaults? opening the black box of relationships. *Journal of Financial Intermediation 31*, 1–15.

Rajan, R. and A. Winton (1995). Covenants and collateral as incentives to monitor. *The Journal of Finance 50*(4), 1113–1146.

Rampini, A. A. and S. Viswanathan (2010). Collateral, risk management, and the distribution of debt capacity. *The Journal of Finance 65*(6), 2293–2322.

Rampini, A. A. and S. Viswanathan (2013). Collateral and capital structure. *Journal of Financial Economics 109*(2), 466–492.

Roberts, M. (2015). The role of dynamic renegotiation and asymmetric information in financial contracting. *Journal of Financial Economics 116*(1), 61–81.

Roberts, M. and A. Sufi (2009). Control rights and capital structure: An empirical investigation. *The Journal of Finance 64*(4), 1657–1695.

Santos, J. A. C. and S. Viswanathan (2020). Bank syndicates and liquidity provision. *Working paper*.

Smith Jr, C. W. and J. B. Warner (1979). On financial contracting: An analysis of bond covenants. *Journal of financial economics 7*(2), 117–161.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The journal of Finance 57*(5), 1891–1921.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *The American economic review 71*(3), 393–410.

Strahan, P. E. (1999). Borrower risk and the price and nonprice terms of bank loans. *FRB of New York staff report* (90).

Stulz, R. and H. Johnson (1985). An analysis of secured debt. *Journal of financial Economics 14*(4), 501–521.

Sufi, A. (2009, 01). Bank Lines of Credit in Corporate Finance: An Empirical Analysis. *The Review of Financial Studies 22*(3), 1057–1088.

Thakor, A. V. and G. F. Udell (1991). Secured lending and default risk: equilibrium analysis, policy implications and empirical results. *The Economic Journal 101*(406), 458–472.

Tirole, J. (2012). Overcoming adverse selection: How public intervention can restore market functioning. *American Economic Review 102*(1), 29–59.

Wang, Y., T. M. Whited, Y. Wu, and K. Xiao (2020). Bank market power and monetary policy transmission: Evidence from a structural estimation. Technical report, National Bureau of Economic Research.

Whited, T. M. and G. Wu (2006, 01). Financial Constraints Risk. *The Review of Financial Studies 19*(2), 531–559.

Bank Liquidity Provision Across the Firm Size Distribution
Online Appendix

A Additional Tables

Table A.1: *Comparing Y-9C and Y14 Aggregate Credit in $B*

Dataset	2019q4				2020q1				2020q2			
Description	Comm.	Util.	No. Banks	No. Obs	Comm.	Util.	No. Banks	No. Obs	Comm.	Util.	No. Banks	No. Obs
Y-9C All Banks:												
All Loans	4,608	2,254	350		4,627	2,565	349		4,833	2,573	345	
C&I	3,805	1,705	345		3,826	2,015	345		4,039	2,022	341	
Of which: $> 1m$	3,533	1,449	347		3,552	1,753	346		3,611	1,623	343	
Real estate-backed	631	377	340		633	381	340		626	382	337	
Of which: $> 1m$	496	242	341		501	249	341		494	250	338	
Other Leases	126	126	120		125	125	129		123	123	129	
Agricultural	46	46	247		44	44	245		46	46	244	
Y-9C Final Sample:												
All Loans	3,536	1,557	29		3,533	1,829	29		3,608	1,733	29	
C&I	3,124	1,274	29		3,125	1,549	29		3,207	1,457	29	
Of which: $> 1m$	2,959	1,109	29		2,959	1,383	29		2,961	1,211	29	
Real estate-backed	298	169	29		298	169	29		293	169	29	
Of which: $> 1m$	249	119	29		249	121	29		246	122	29	
Other Leases	101	101	26		99	99	26		96	96	26	
Agricultural	13	13	22		12	12	22		11	11	22	
Y-14Q Original Aggregate	4,613	1,997	32	270748	4,639	2,348	32	266749	4,624	2,073	32	267384
Y-14Q H1 Final Sample:												
All Loans	2,772	1,175	29	171034	2,796	1,428	29	169699	2,750	1,223	29	170892
C&I	2,585	1,006	29	126921	2,610	1,260	29	126015	2,561	1,052	29	125236
Real estate-backed	117	110	28	31846	118	111	28	31842	123	116	28	33997
Other Leases	56	51	25	10092	54	49	25	9784	52	47	25	9685
Agricultural	14	8	20	2175	14	7	20	2058	13	7	20	1974

Notes: This table reports the aggregate amount of committed and utilized bank credit in the FR-Y9C and the FR-Y14 H1 in the quarter reported in the header. The rows under the header "Y-9C All Banks" contain all loans listed in Y-9C schedule HC-C item 4.a (C&I loans to U.S. addresses), item 1.e(1) (loans secured by owner-occupied nonfarm nonresidential properties), item 10.b (other leases), or item 3 (loans to finance agricultural production). The rows labeled "Of which: $> 1m$" restrict to loans with commitments above $1 million using the Call Report small business lending schedule RC-C Part II. The rows under the header "Y-9C Final Sample" restrict to banks in our final Y-14 sample. The row labeled "Y-14Q Original Aggregate" contains all loans in the Y-14 Schedule H-1, including to borrowers in finance, insurance, and real estate (NAICS 52, 5312, or 551111) and from banks not in our final balanced sample that report consistently through 2020Q2. The rows under the header "Y-14Q Final Sample" contain our final sample of loans from a consistent panel of banks and corresponding to the four schedule HC-C items listed above.

Table A.2: ***Frequency of Borrower Financial Updates Controlling for Loan Characteristics.***

Dependent variable	Financials Indicator			Audit Indicator		
	(1)	(2)	(3)	(4)	(5)	(6)
<50m	0.41***			0.24***		
	(0.001)			(0.001)		
50-250m	0.49***	0.07***	0.07***	0.25***	0.02***	0.02***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
250m-1bn	0.49***	0.09***	0.09***	0.30***	0.07***	0.06***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
1-5bn	0.56***	0.12***	0.13***	0.39***	0.13***	0.13***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
>5bn	0.62***	0.13***	0.16***	0.44***	0.16***	0.15***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Bank-Time FE	No	Yes	Yes	No	Yes	Yes
Industry-Time FE	No	No	Yes	No	No	Yes
Rating-Time FE	No	No	Yes	No	No	Yes
Loan Controls	No	No	Yes	No	No	Yes
No of Loans	142209	142090	141989	91252	91233	91208
N	1077566	1076699	1076107	633202	632968	632823
R^2	.023	.407	.411	.027	.367	.371

Notes: Regresses an indicator for updated reported financials in last two quarters (Col. 1-3) and reported audited financials in last two quarters (Col. 4-6) on various controls. Loan controls include maturity indicators, and collateral indicators. Sample is 2015Q1-2019Q4. Excludes bank-quarters that rarely report audit dates. Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.3: *Median Volatility Across the Firm Size Distribution*

Standard deviation:	Revenue growth		EBITDA/Assets		Net income/Assets		Stock return	
	Raw	Demeaned	Raw	Demeaned	Raw	Demeaned	Raw	Demeaned
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.28^{**}	0.25^{**}	0.16^{**}	0.16^{**}	0.19^{**}	0.24^{**}	0.17^{**}	0.17^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
50-250	-0.05^{**}	-0.05^{**}	-0.06^{**}	-0.06^{**}	-0.08^{**}	-0.13^{**}	-0.03^{+}	-0.03^{*}
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
250-1000	-0.10^{**}	-0.11^{**}	-0.09^{**}	-0.09^{**}	-0.12^{**}	-0.16^{**}	-0.05^{**}	-0.05^{**}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
1000-5000	-0.11^{**}	-0.11^{**}	-0.10^{**}	-0.11^{**}	-0.14^{**}	-0.18^{**}	-0.07^{**}	-0.08^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
5000+	-0.13^{**}	-0.12^{**}	-0.11^{**}	-0.12^{**}	-0.15^{**}	-0.19^{**}	-0.09^{**}	-0.09^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Observations	2,077	2,039	2,027	1,989	2,077	2,039	1,125	1,125

Notes: Each column reports the coefficients from a quantile regression on a constant and indicators for four size bins, in millions of dollars. Thus, the coefficient in the first row gives the median standard deviation of the variable indicated in the column header for firms with less than $50 million in assets, and the subsequent rows give the difference in the median standard deviation between firms with less than $50 million in assets and firms in the size category indicated in the first column. The sample in columns (1)-(6) is a balanced panel of Compustat firms over fiscal years 1995-2015, excluding firms in finance (NAICS 52, 5312, or 551111) or with non-positive revenue or assets in any year. All Compustat variables are deflated using the GDP price index. The sample in columns (7)-(8) is the subset of these firms with non-missing stock return information in all months between 1995 and 2015, using the WRDS CRSP-Compustat link. The dependent variable in columns (1), (3), (5), and (7) is the raw standard deviation over the 1995-2015 period. The dependent variable in columns (1), (3) and (5) is the standard deviation after first demeaning the variable with respect to industry (NAICS 4)-year. The dependent variable in column (8) is the standard deviation of the excess return over the CRSP value-weighted index. Robust standard errors in parentheses.

Table A.4: *Distribution of Collateral Use by Industry and Facility Type, December 31, 2019*

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets (mil.)								
Panel A: Revolving Credit Lines								
11: Agriculture, Forestry, Fishing, Hunting	.016	.015	.47	.062	.081	.28	.079	1436
21: Mining, Quarrying, Oil, Gas.	.017	.037	.35	.051	.26	.11	.18	2196
22: Utilities	.00098	.032	.035	.016	.095	.088	.73	2047
23: Construction	.013	.027	.33	.053	.062	.38	.13	3789
31-33: Manufacturing	.01	.02	.36	.037	.066	.27	.24	14953
42: Wholesale Trade	.011	.013	.5	.021	.04	.33	.093	9634
44-45: Retail Trade	.028	.0082	.67	.012	.028	.15	.11	7092
48-49: Transportation and Warehousing	.017	.019	.26	.11	.082	.26	.25	2466
51: Information	.0049	.038	.23	.016	.12	.32	.27	2060
53: Real Estate and Rental and Leasing	.045	.06	.17	.097	.081	.11	.44	2173
54: Professional, Scientific, and Technical Services	.004	.023	.36	.01	.06	.41	.14	4968
55: Management of Companies and Enterprises	.014	.13	.23	.014	.037	.3	.3	296
56: Administrative ...	.0088	.029	.35	.028	.087	.4	.11	1931
61: Educational Services	.098	.037	.22	.018	.18	.34	.12	164
62: Health Care and Social Assistance	.055	.03	.32	.022	.087	.4	.1	1546
71: Arts, Entertainment, and Recreation	.042	.053	.2	.12	.16	.31	.11	813
72: Accommodation and Food Services	.051	.042	.17	.044	.2	.32	.18	1083
81: Other Services	.063	.06	.27	.026	.078	.32	.18	464
Panel B: Term Loans								
11: Agriculture, Forestry, Fishing, Hunting	.2	.027	.13	.42	.088	.097	.033	331
21: Mining, Quarrying, Oil, Gas.	.085	.0073	.22	.34	.075	.18	.087	412
22: Utilities	.035	.082	.078	.26	.078	.2	.27	548
23: Construction	.24	.01	.1	.41	.026	.18	.045	1904
31-33: Manufacturing	.23	.013	.13	.23	.044	.24	.12	8449
42: Wholesale Trade	.38	.0073	.12	.16	.033	.25	.055	3849
44-45: Retail Trade	.48	.0046	.24	.044	.013	.18	.044	5713
48-49: Transportation and Warehousing	.13	.0018	.054	.64	.039	.087	.047	3267
51: Information	.11	.024	.14	.14	.1	.36	.13	1157
53: Real Estate and Rental and Leasing	.57	.0067	.023	.15	.03	.16	.067	5711
54: Professional, Scientific, and Technical Services	.23	.011	.16	.12	.051	.36	.081	2083
55: Management of Companies and Enterprises	.55	.0096	.046	.099	.0096	.22	.065	415
56: Administrative ...	.23	.0078	.15	.21	.04	.31	.061	895
61: Educational Services	.61	.017	.042	.047	.038	.22	.025	236
62: Health Care and Social Assistance	.38	.011	.11	.11	.051	.29	.058	2322
71: Arts, Entertainment, and Recreation	.38	.029	.071	.21	.059	.21	.036	984
72: Accommodation and Food Services	.2	.015	.071	.057	.066	.57	.029	2552
81: Other Services	.64	.013	.034	.055	.021	.2	.05	776

Notes: The table reports the fraction of loan commitments to each industry with the type of collateral indicated in the table header. The sample includes all loans in the Y-14 corporate loan schedule as of 2019Q4. We exclude from this table any industry with fewer than 40 loans in our sample as of December 31, 2019.

Table A.5: ***Collateral Usage in Credit Lines by Firms Size and Industry.***

Dependent variable	AR+Inventory		Real Estate		Fixed Assets		Cash		Other		Blanket Lien		Unsecured	
	Credit Lines													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
50-250 (in mil)	-0.105***	-0.049***	0.005*	0.004	0.029***	0.024***	0.011***	0.008***	0.026***	0.014***	-0.053***	-0.082***	0.089***	0.083***
	(0.007)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
250-1000 (in mil)	-0.198***	-0.107***	-0.004*	-0.007***	0.026***	0.017***	0.028***	0.022***	0.039***	0.016***	-0.089***	-0.134***	0.201***	0.195***
	(0.009)	(0.009)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)
1000-5000 (in mil)	-0.259***	-0.156***	-0.012***	-0.014***	0.007*	-0.001	0.029***	0.022***	0.054***	0.026***	-0.144***	-0.191***	0.325***	0.315***
	(0.009)	(0.009)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.008)	(0.012)	(0.012)
>5000 (in mil)	-0.451***	-0.330***	-0.015***	-0.017***	-0.015***	-0.024***	0.006**	-0.000	0.025***	-0.001	-0.239***	-0.281***	0.686***	0.652***
	(0.008)	(0.011)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.006)	(0.008)	(0.014)	(0.016)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No of Firms	40602	40602	40602	40602	40602	40602	40602	40602	40602	40602	40602	40602	40602	40602
N	60559	60559	60559	60559	60559	60559	60559	60559	60559	60559	60559	60559	60559	60559
R^2	0.097	0.208	0.003	0.009	0.006	0.023	0.007	0.016	0.007	0.032	0.036	0.100	0.331	0.351
	Term Loans													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
50-250 (in mil)	0.015*	0.016*	-0.204***	-0.188***	0.191***	0.140***	0.006**	0.007***	0.014***	0.017***	-0.026**	0.002	0.000	0.002
	(0.006)	(0.006)	(0.009)	(0.008)	(0.011)	(0.009)	(0.002)	(0.002)	(0.003)	(0.003)	(0.008)	(0.007)	(0.002)	(0.003)
250-1000 (in mil)	0.002	0.012	-0.308***	-0.290***	0.253***	0.187***	0.015***	0.016***	0.023***	0.024***	-0.022	0.012	0.035***	0.037***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.021)	(0.018)	(0.003)	(0.003)	(0.005)	(0.005)	(0.013)	(0.011)	(0.006)	(0.006)
1000-5000 (in mil)	0.026*	0.024*	-0.373***	-0.341***	0.054**	0.022	0.026***	0.026***	0.052***	0.050***	0.006	0.017	0.204***	0.199***
	(0.011)	(0.012)	(0.010)	(0.010)	(0.018)	(0.016)	(0.005)	(0.005)	(0.007)	(0.007)	(0.018)	(0.018)	(0.019)	(0.019)
>5000 (in mil)	-0.036***	-0.040***	-0.421***	-0.375***	0.056**	0.031	0.013***	0.011**	0.046***	0.041***	-0.086***	-0.087***	0.424***	0.416***
	(0.009)	(0.011)	(0.006)	(0.009)	(0.017)	(0.018)	(0.004)	(0.004)	(0.007)	(0.008)	(0.017)	(0.018)	(0.028)	(0.029)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No of Firms	20690	20690	20690	20690	20690	20690	20690	20690	20690	20690	20690	20690	20690	20690
N	31591	31591	31591	31591	31591	31591	31591	31591	31591	31591	31591	31591	31591	31591
R^2	0.002	0.047	0.115	0.188	0.056	0.209	0.006	0.011	0.008	0.017	0.003	0.084	0.203	0.212

Notes: Results from estimating a model of the following type:

$$\text{collateral class}_\ell = \sum_{j \neq \{\$0\text{-}50\}} \beta_j \mathbb{1}\{\text{size class} = j\} + \text{Industry FE} + \epsilon_\ell$$

where post-2020Q1 is a dummy that is one after 2020Q1. Data for 2019Q4. Robust standard errors are clustered at the bank level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.6: ***Distribution of Cash / Assets by Firm as of December 31, 2019***

Firm Size	Cash / Assets						
(Assets in Millions)	10^{st} Percentile	25^{th} Percentile	Mean	Median	75^{th} Percentile	90^{th} Percentile	Firms in Category
<50	0.3	2.1	12.9	7.6	17.4	32.4	19,274
50-250	0.1	1.1	9.0	4.5	12.5	23.4	5,360
250-1000	0.2	1.2	8.8	3.5	10.5	23.0	2,385
1000-5000	0.3	0.9	6.7	3.1	8.1	16.4	1,774
5000-	0.2	0.9	6.2	3.0	7.5	15.4	1,329

Notes: The table reports the distribution of individual borrowers' cash and equivalents divided by total assets with financial reporting available as of December 31, 2019. For firms matched to Compustat, cash and equivalents and total assets are sourced from Compustat financials.

Table A.7: ***Pricing of Revolving Credit Lines and Market Concentration.***

Dependent variable	Interest Rate (in bp)					
Sample	All Revol. Cl.	HHI>p50	HHI<p50	HHI>p50	HHI<p50	New Relationship
50-250 (in mil)	-35.6***	-52.6***	-28.9***	-43.6***	-35.0***	-10.8**
	(1.648)	(2.812)	(1.916)	(4.215)	(1.775)	(5.239)
250-1000 (in mil)	-36.0***	-56.2***	-31.5***	-48.9***	-34.5***	9.2
	(2.828)	(5.030)	(3.151)	(6.293)	(3.100)	(7.816)
1000-5000 (in mil)	-61.6***	-79.2***	-57.9***	-58.7***	-62.4***	-30.5**
	(2.715)	(6.918)	(2.877)	(6.166)	(2.965)	(13.072)
>5000 (in mil)	-84.7***	-110.4***	-78.9***	-99.1***	-83.2***	-28.1**
	(4.481)	(15.485)	(4.652)	(9.442)	(4.997)	(13.307)
HHI Data Source	None	Y-14	Y-14	SOD	SOD	None
Avg. Sample HHI	.176	.369	.113	.408	.148	.156
Median County HHI	.181	.181	.181	.275	.275	.181
Reference-Rate-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Financial Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Term Controls	No	No	No	No	No	No
No. Firms	38683	10009	30276	5531	33329	5531
No. Obs	123613	30452	92533	15807	103307	6167
R^2	.547	.649	.535	.664	.541	.678

Notes: Results from estimating a model of the following type: $\text{Interest}_{\ell,t} = \sum_{s\neq\{\$0-50m\}} \beta_{1,s}\mathbb{I}\{\text{size class} = s\} + \Gamma' X_t + \epsilon_{\ell,t}$ where $\text{Interest}_{\ell,i,b,t}$ is the interest on facility ℓ from bank b to firm i at time t. The sample contains originations and renewals between 2015Q1 and 2019Q4. Industry×time fixed effects are at the NAICS 3-digit level. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense. Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.8: ***Total Debt Increase between December 31, 2019 and March 31, 2020***

	2019q4			2020q1		
Firm Size	Debt	Bk. Loan	No. Obs	Debt	Bk. Loan	No. Obs
<50	30.91	26.47	3062	31.04	26.07	3062
50-250	43.14	29.50	867	44.28	28.07	867
250-1000	127.18	45.63	577	129.48	49.42	577
1000-5000	655.08	123.72	665	685.42	146.19	665
5000-	2,590.25	156.26	526	2,665.65	232.25	526

Notes: This table represents the change in total debt for a balanced panel of firms that for which financial information is available as of Dec. 31, 2019 and March 31, 2020. Financial information is sourced from Compustat, where available, and the FR Y-14Q Schedule H1 otherwise. Total debt represents the sum of long-term and short-term debt. Bank loans represent the global commitment of banking credit.

Table A.9: *Drawdowns by Firm Size: Details on Maturity, Collateral, and Interest Rate Controls*

Dependent Variable	Drawdown Rate (in ppt)	
	(1)	(2)
Demand Loans × COVID	-4.3***	-2.3***
	(0.5)	(0.8)
1-6 month × COVID	0.0	0.0
	(.)	(.)
6-12 month × COVID	0.8**	0.6*
	(0.4)	(0.4)
1-2 years × COVID	2.2**	1.7**
	(0.8)	(0.7)
2-4 years × COVID	6.1***	4.1***
	(1.3)	(1.0)
More than 4 years × COVID	7.4***	5.4***
	(1.3)	(0.9)
Real Estate × COVID	-1.2	0.0
	(1.4)	(1.1)
Cash × COVID	-0.8	-0.6
	(0.6)	(0.5)
AR+Inventory × COVID	-2.1***	-1.3***
	(0.4)	(0.3)
Fixed Assets × COVID	-0.6	-0.2
	(0.6)	(0.6)
Other × COVID	-0.2	-0.2
	(0.7)	(0.7)
Unsecured × COVID	0.0	0.0
	(.)	(.)
Spread × COVID		215.6***
		(81.5)
20-40% Drawdown 2019Q4 × COVID		-1.5
		(2.5)
40-60% Drawdown 2019Q4 × COVID		-2.0
		(4.1)
60-80% Drawdown 2019Q4 × COVID		-15.3**
		(6.5)
80-100% Drawdown 2019Q4 × COVID		-6.8***
		(1.0)
Loan FE	Yes	Yes
Time FE	No	No
Bank-Time FE	Yes	Yes
State-Time FE	Yes	Yes
Industry-Time FE	Yes	Yes
Financials	Yes	Yes
Rating-Time FE	Yes	Yes
Maturity Controls	Yes	Yes
Collateral Controls	Yes	Yes
Interest Rate Controls	No	Yes
Drawdown in 2019q4	No	Yes
No of Firms	60195	43654
N	756540	549043
R^2	.83	.83

Notes: Results from estimating a model of the following type: $\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_{s,1} \left[\mathbb{I}\{\text{size class} = s\}\right] \times \text{COVID} + \Gamma' \times X_\ell \times \text{COVID} + \epsilon_{\ell,t}$ where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit and COVID is an indicator for 2020Q1 and 2020Q2. We restrict the sample to outstanding loans from 2017Q4 onwards. Industry×time fixed effects are at the NAICS 3 digit level. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are lagged debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense, each interacted with COVID. Maturity and collateral controls are six maturity categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years) and six collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), each interacted with COVID. Robust standard errors are clustered at the three digit NAICS level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.10: ***Drawdown of Revolving Credit Lines by Firm Size, 2020Q1 and 2020Q2***

	Utilization/Commitment						
Assets (mil.)	$< 10\%$	10− 30%	30− 50%	50− 70%	70− 90%	$> 90\%$	Obs.
			Panel A: 2020Q1				
0-50	.3	.087	.12	.15	.14	.19	36391
50-250	.29	.095	.12	.16	.15	.18	10803
250-1000	.27	.1	.14	.17	.16	.16	8132
1000-5000	.28	.16	.15	.14	.12	.15	9473
>5000	.53	.12	.094	.078	.044	.14	8688
			Panel B: 2020Q2				
0-50	.41	.11	.16	.12	.071	.13	35073
50-250	.37	.12	.15	.14	.092	.14	10796
250-1000	.34	.12	.15	.13	.1	.15	8220
1000-5000	.4	.15	.13	.11	.068	.14	9563
>5000	.67	.084	.057	.041	.024	.12	9021

Notes: The table reports the distribution of drawn credit as a share of total commitments. The distribution is reported for 2020Q1 and 2020Q2. Observations report the number of loans in each size category in 2020Q1 and 2020Q2, respectively.

Table A.11: ***Drawdowns by Firm Size and Exposure to COVID-19 shock: Abnormal 3-digit Industry Decline in Sales.***

Dependent variable	Drawdown Rate (in ppt)					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × COVID	11.0**	6.3*	5.0*	5.1**	4.8**	-5.5***
	(4.0)	(3.5)	(2.4)	(2.2)	(2.0)	(1.7)
Exposure × 50-250 (in mil) × COVID		5.4***	4.9***	5.1***	5.2***	1.2
		(1.2)	(1.2)	(1.1)	(1.2)	(2.0)
Exposure × 250-1000 × COVID		2.8	3.5**	3.5**	3.6**	1.6
		(2.1)	(1.4)	(1.3)	(1.4)	(2.1)
Exposure × 1000-5000 × COVID		6.8	7.9**	7.8**	7.9**	4.4
		(4.0)	(3.2)	(3.1)	(3.1)	(3.8)
Exposure × 5000- × COVID		8.5	9.9	9.3	9.7	7.5
		(7.7)	(6.8)	(6.5)	(6.2)	(6.1)
50-250 (in mil) × COVID		3.4**	2.3**	2.2**	2.2**	0.5
		(1.5)	(0.8)	(0.8)	(0.9)	(0.7)
250-1000 × COVID		6.5**	5.2**	4.7**	4.9**	0.9
		(2.6)	(1.8)	(1.8)	(1.8)	(0.9)
1000-5000 × COVID		17.8***	16.0***	15.7***	15.6***	8.6***
		(3.9)	(3.1)	(3.0)	(2.8)	(2.1)
5000- × COVID		28.9***	25.1***	25.7***	25.6***	16.2**
		(6.7)	(6.5)	(6.4)	(6.3)	(5.4)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No
Bank-Time FE	No	No	Yes	Yes	Yes	Yes
State-Time FE	No	No	No	Yes	Yes	Yes
Financials	No	No	No	No	Yes	Yes
Rating-Time FE	No	No	No	No	Yes	Yes
Loan Terms	No	No	No	No	No	Yes
No of Firms	14591	14591	14591	14591	13484	9196
N	184903	184903	184892	184891	168344	124123
R^2	0.81	0.81	0.81	0.82	0.83	0.81

Notes: Results from estimating a model of the following type:

$$\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \sum_{s\neq\{\$0-50m\}} \beta_{1,s}\left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \beta_2\left[\text{Exposure}_i \times \text{COVID}\right]$$
$$+ \sum_{s\neq\{\$0-50m\}} \beta_{3,s}\left[\text{Exposure} \times \mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \epsilon_{\ell,i,t}.$$

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2 and Exposure_i is the 3-digit NAICS code industry-level growth in sales between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. Financial controls include leverage (total debt / assets), interest coverage (operating income / interest expense), return on assets (net income / assets), access to cash (cash and receivables / assets), and whether the borrower is active in the bond market. Loan term controls include maturity, collateral type, interest rate spread and drawdown levels in 2019q4. For loan term controls, we consider 6 maturity class categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years), 6 types of collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), 5 categories of drawdown prior to COVID (<20%, 20-40%, 40-60%, 60-80%, and >80%), and interest rate spreads; we allow effects of these controls to vary pre- and post-COVID shock. We restrict the sample to outstanding loans from 2017Q4 onwards. Sales data only avaiable for retail sales and restaurants. Robust standard errors are clustered at the 3-digit NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.12: ***Drawdowns by Firm Size Category - Controlling for Bank Balance Sheet Constraints***

Dependent Variable Drawdown Rate (in ppt)				
BANK Variable	N/A	CET1 > p50	Liq. > p50	Fund. > p50
	(1)	(2)	(3)	(4)
BANK × COVID		2.5*	2.0	-1.0
		(1.2)	(1.2)	(1.0)
BANK × 50-250 (in mil) × COVID		-1.5	-5.3***	2.4
		(1.5)	(1.3)	(1.9)
BANK × 250-1000 × COVID		4.1*	-4.3**	1.8
		(2.0)	(1.9)	(2.3)
BANK × 1000-5000 × COVID		3.0	-0.6	0.2
		(2.0)	(1.6)	(1.7)
BANK × 5000- × COVID		1.1	-1.2	0.6
		(1.8)	(1.4)	(1.3)
50-250 (in mil) × COVID	3.9**	4.5***	6.8***	2.4**
	(1.6)	(1.5)	(1.2)	(0.9)
250-1000 × COVID	10.2***	9.5***	12.4***	8.9***
	(1.9)	(1.6)	(1.7)	(1.7)
1000-5000 × COVID	12.7***	11.6***	12.4***	12.0***
	(1.6)	(1.4)	(1.5)	(1.6)
5000- × COVID	13.9***	13.6***	14.7***	13.9***
	(1.6)	(1.6)	(1.7)	(1.4)
Median BANK Value	N/A	11.797	29.175	43.285
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Firm Financials Controls	No	Yes	Yes	Yes
Rating-Time FE	No	Yes	Yes	Yes
Loan FE	Yes	Yes	Yes	Yes
Loan Term Controls	No	No	No	No
Interest Rate Spread	No	No	No	No
No. Firms	55129	49739	49739	49739
No. Obs	727616	593074	593074	593074
R^2	.819	.826	.826	.826

Notes: Results from estimating a model of the following type:

$$\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \gamma_i + \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \beta_2 \left[\text{BANK}_i \times \text{COVID}\right]$$
$$+ \sum_{s \neq \{\$0-50m\}} \beta_{3,s} \left[\text{BANK} \times \mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \epsilon_{\ell,i,t}.$$

where $\text{Drawdown}_{\ell,i,t}$ is the ratio of utilized over committed credit on loan ℓ at time t by bank i, COVID is an indicator variable for observations in and after 2020Q1 and BANK_i represents the relevant bank balance sheet constraint from the prior quarter. Bank balance sheet constraints include discrete variables indicating whether a bank has above median CET1 ratio (CET1 / RWA), Liquid Assets, or Core Deposits in a given quarter t compared to other banks in the sample, in columns (2), (3), and (4), respectively. Median BANK Value indicates the average median value for the relevant bank balance sheet constraint. For the purposes of this analysis, we excluded all loans held at banks that are U.S. subsidiaries of foreign banks. Robust standard errors are clustered at the bank-level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.13: ***PPP Participation and COVID Exposure and Loan Terms.***

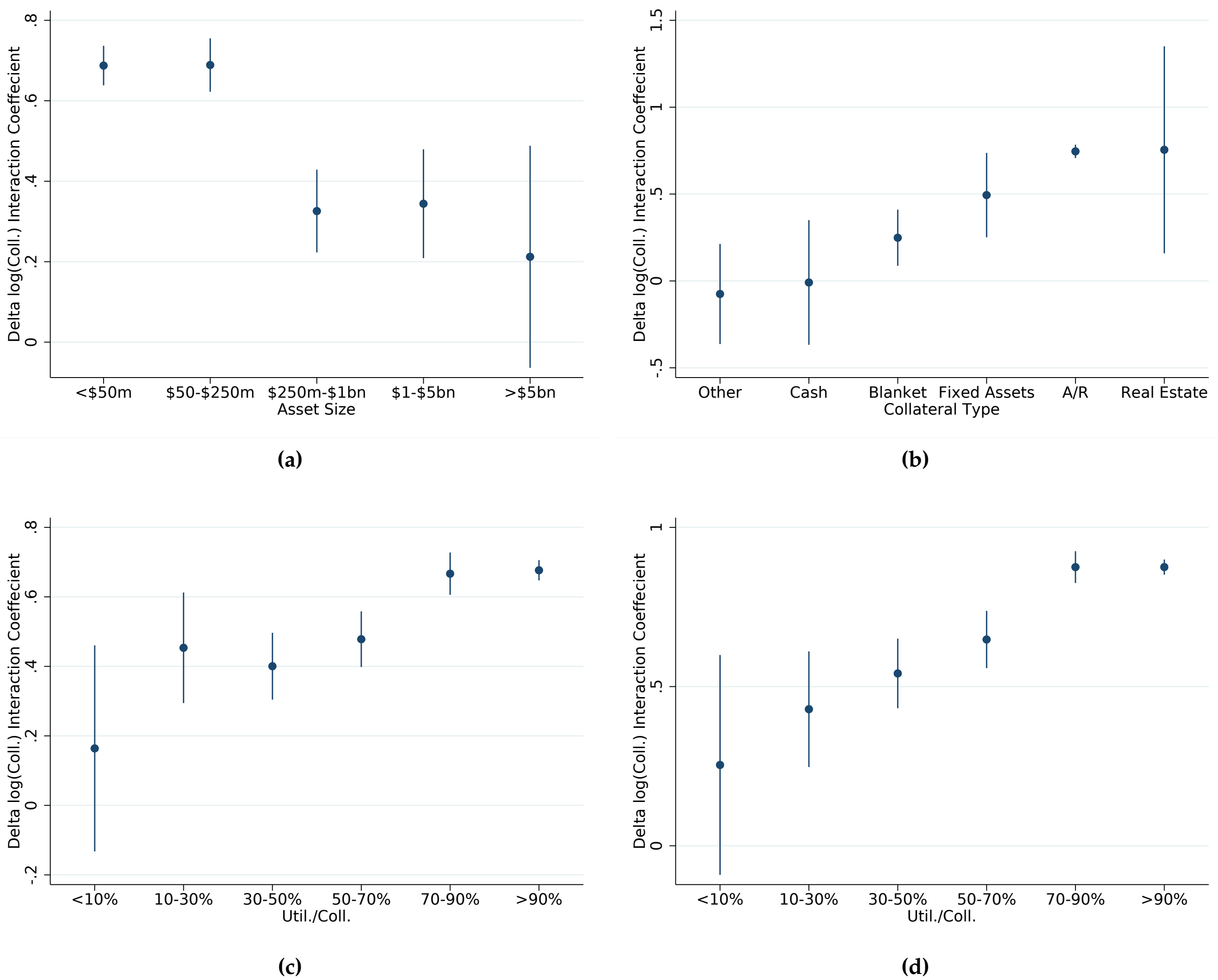
Sample	<250	0-50	50-250	<250	0-50	50-250
Dependent variable	PPP Participation					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.030***	0.028***	0.028***	0.018***	0.017***	0.018**
	(0.004)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)
log(Assets)	-0.055***	0.041***	-0.232***	-0.036***	0.042***	-0.196***
	(0.002)	(0.003)	(0.010)	(0.002)	(0.003)	(0.010)
Drawdown 2020Q1				0.014*	-0.008	0.115***
				(0.006)	(0.007)	(0.013)
Demand Loans				0.064***	0.061***	0.082***
				(0.008)	(0.008)	(0.021)
6-12 month				-0.050***	-0.047***	0.011
				(0.008)	(0.009)	(0.024)
1-2 years				-0.014	-0.009	-0.029
				(0.008)	(0.009)	(0.023)
2-4 years				-0.062***	-0.043***	-0.074***
				(0.009)	(0.011)	(0.021)
More than 4 years				-0.196***	-0.146***	-0.141***
				(0.011)	(0.015)	(0.021)
Real Estate				-0.060***	-0.105***	-0.013
				(0.017)	(0.020)	(0.033)
Cash				-0.162***	-0.204***	-0.034
				(0.019)	(0.024)	(0.031)
AR+Inventory				0.081***	0.055***	0.107***
				(0.005)	(0.006)	(0.011)
Fixed Assets				0.111***	0.057***	0.181***
				(0.013)	(0.016)	(0.021)
Other				-0.008	-0.021	0.023
				(0.011)	(0.012)	(0.020)
No of Firms	36656	29350	7370	36399	29098	7365
N	43060	33393	9667	42796	33135	9661
R^2	0.020	0.007	0.049	0.061	0.033	0.109

Notes: This tables shows results from estimating a model of the following type:

$$\text{PPP Participation}_{i,t} = \alpha_\ell + \delta_t + \beta_t \times \text{Exposure}_i + \epsilon_{\ell,i,t}$$

Robust standard errors are clustered at the three digits NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

B Additional Figures



(a) (b) (c) (d)

Figure A.1: *The figures above plot coefficients estimated using a loan-level panel regression of the change in the log of utilization on the change in log collateral values in the presence of various controls:* $\Delta \ln \mathit{Utilization}_{\ell,t} = \sum_s \beta_s \left[\mathbb{I}\{\mathit{size\ class} = s\} \times \Delta \ln \mathit{Collateral\ value}_{\ell,t}\right] + \Gamma' X_{\ell,t} + \epsilon_{\ell,t}$. *Indicator interactions are used to recover elasticities for sub-samples of loans. Controls include bank-time, industry-time, and rating-time fixed effects, as well as uninteracted indicator variables and the change in the log of commitment size. The sample period is 2015Q1 to 2020Q1. Figures plot the elasticity of utilization to collateral, β, for each sub-sample interaction and the 95% confidence interval. Panel (a) interacts plots elasticities by firm size bin, Panel (b) by collateral type, and Panels (c) and (d) with the percent of utilization relative to collateral value. Panel (d) restricts the sample to loans collateralized by accounts receivable. Standard errors are clustered by firm.*

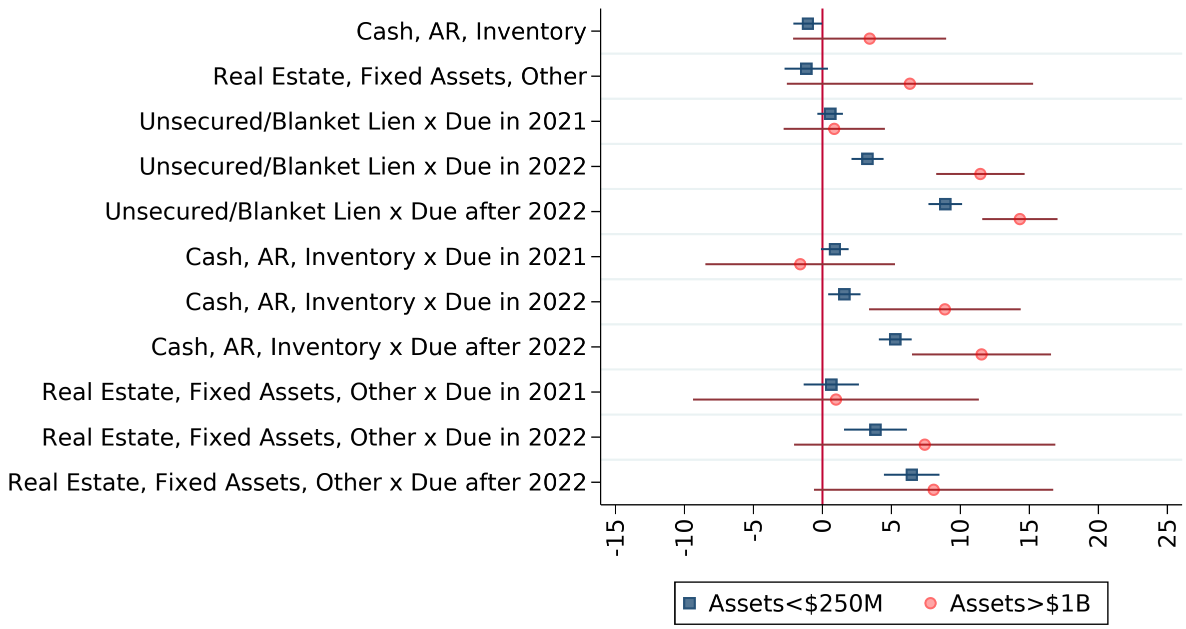
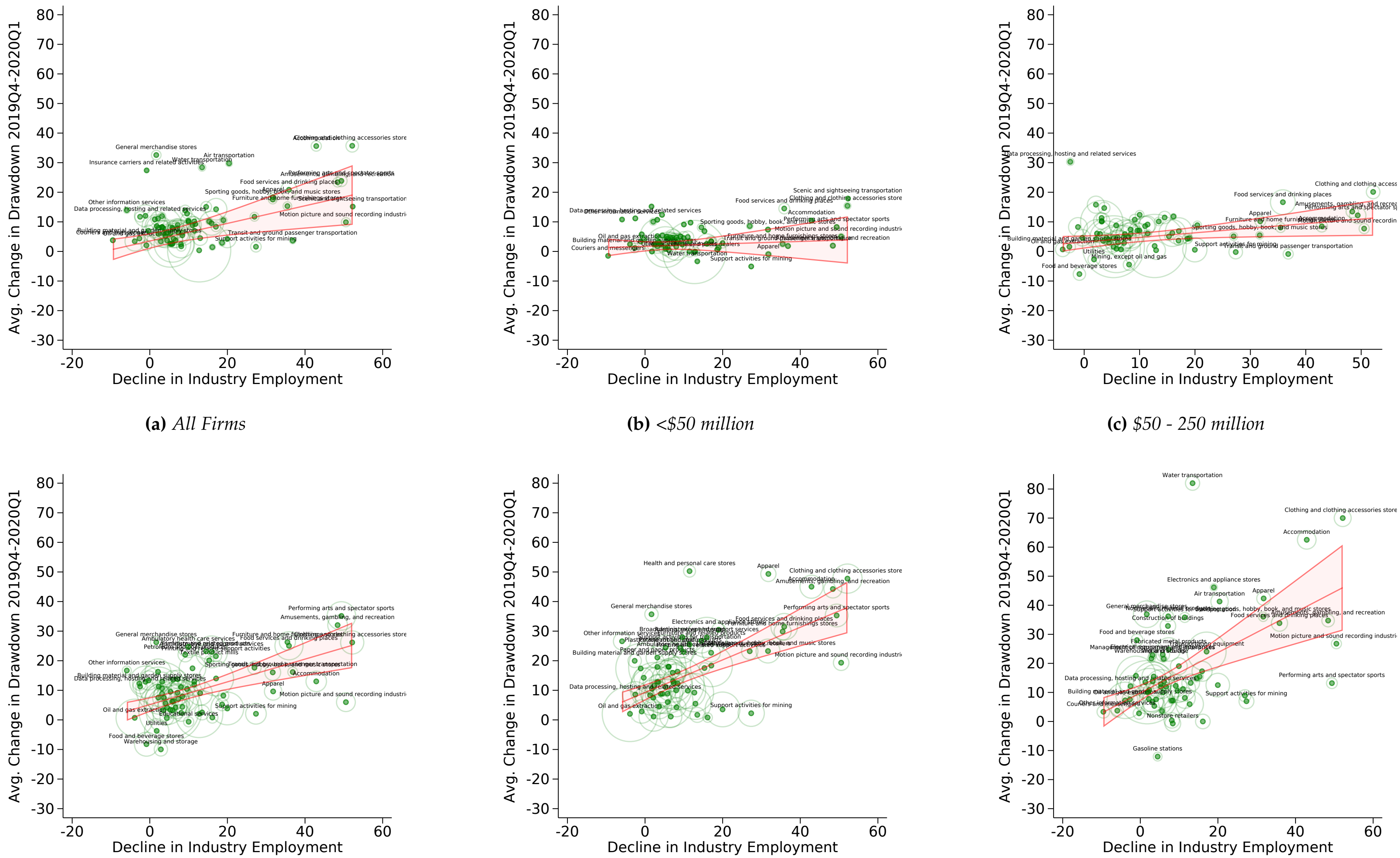


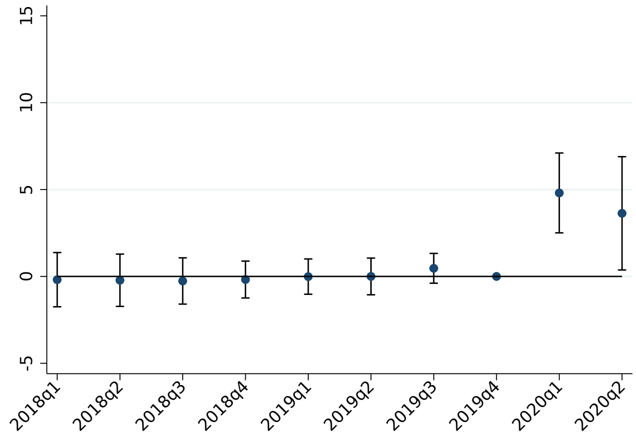
Figure A.2: ***Coefficients on Maturity and Collateral for drawdowns in Q1****. Cross-section regression. Industry, Bank, and Rating, Controls: Financials.*



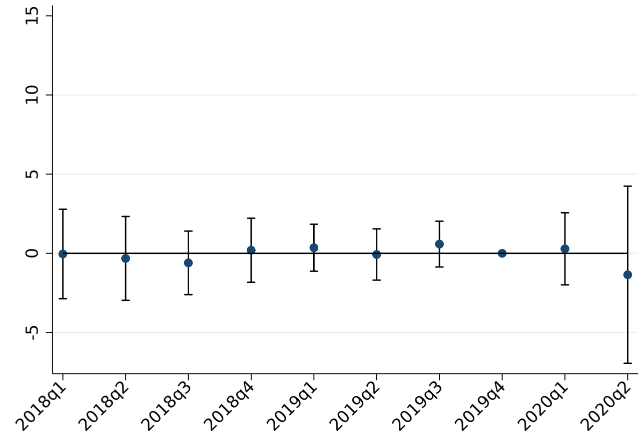
(a) *All Firms* **(b)** *<$50 million* **(c)** *$50 - 250 million*

(d) *$250-1000 million* **(e)** *$1-5 billion* **(f)** *>$5 billion*

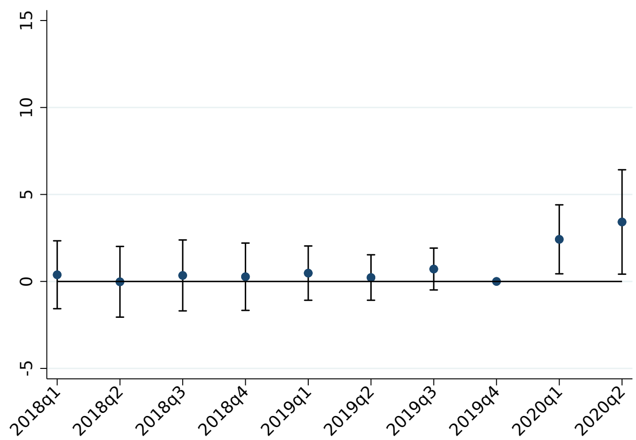
Figure A.3: *Industry COVID Exposure and Credit Line Drawdowns by Firm Size.* *3-digit NAICS code industry-level. Average change in credit line drawdown from 2019Q4 through 2020Q1. Employment growth between 2019Q2 and 2020Q2 less the Q2-to-Q2 average between 2015 and 2019. Linear fit with industries weighted by number of firms per industry. Data restricted to industries with at least 10 firms per firm size category. Perimeter of hollow circles indicate relative industry size by number of firms reporting in the Y14 within the respective size class.*



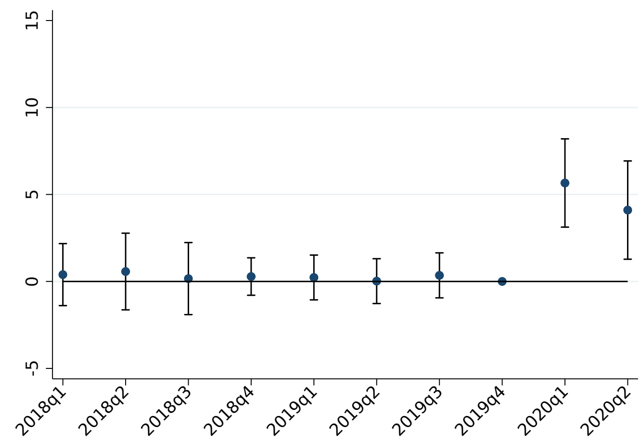
(a) *All Firms*



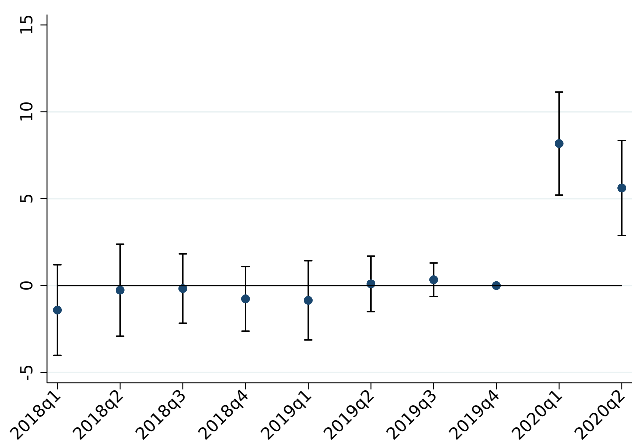
(b) *<$50 million*



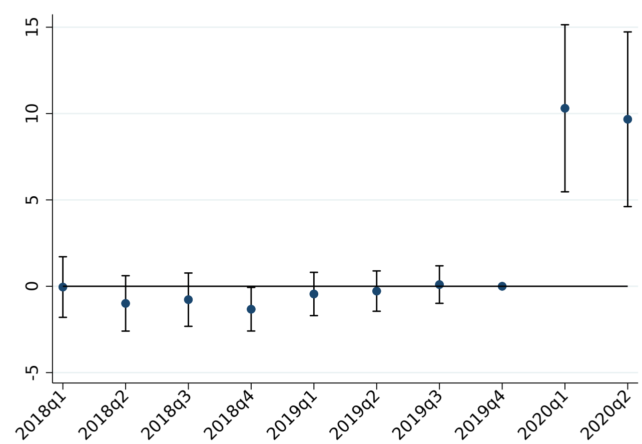
(c) *$50 - 250 million*



(d) *$250-1000 million*

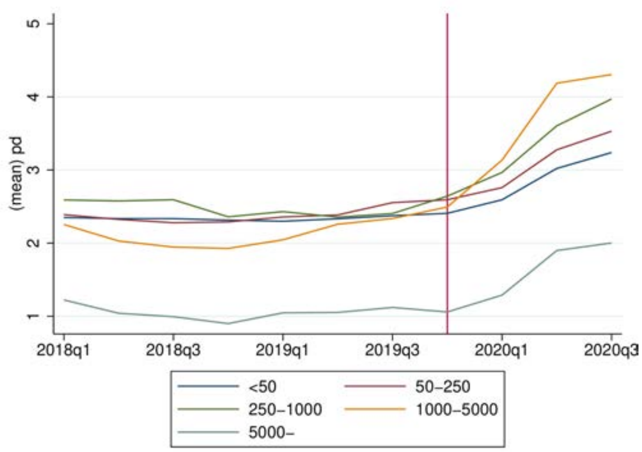


(e) *$1-5 billion*

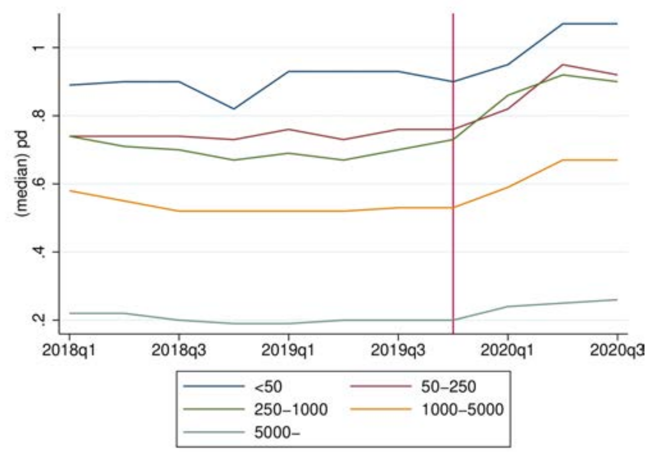


(f) *>$5 billion*

Figure A.4: ***Industry COVID Exposure and Credit Line Drawdowns by Firm Size.*** *The figure plots the sequence of coefficients $\{\beta_t\}$ obtained from estimating $Drawdown_{\ell,t} = \alpha_\ell + \delta_t + \beta_t \times Exposure_i + \epsilon_{\ell,i,t}$, where $Drawdown_{\ell,t}$ is the ratio of utilized to committed credit and $Exposure_i$ is the 3-digit NAICS code industry-level employment growth between 2019Q2 and 2020Q2 less the Q2-to-Q2 average between 2015 and 2019. 95% confidence bands.*



(a) *Mean*



(b) *Median*

Figure A.5: *The figures display the mean and median Probability of Default (PD) values by firm size category over time. Mean and median PD values are based on bank model estimates for borrower PDs, for banks that are required to follow advanced internal ratings based (IRB) approaches, or the corresponding PD based on the borrower's Obligor Risk Rating, for other banks. PD values were adjusted to ensure reporting on a scale of 0-100%. A PD of 100% represent a defaulted borrower. The vertical bar represents 2019q4 (pre-COVID).*

C Proofs and Model Extensions

C.1 Proofs

In order to get close form solutions, assume that ϵ can take three values $\{-e, 0, e\}$ with probability $\{q, 1-2q, q\}$ respectively. The equilibrium contract with discretion is characterized by four regions defined by how large the cash-flow shock ρ is. Two of these are "dominance" regions in the sense that monitoring is not worth it:

- Region 1 (very small shock): $\rho < \theta(z-e)$. In that case, ρ is so small that lender wants to continue even in the worst case scenario ($\theta(z-e) - \rho > 0$). There is thus no value in learning.
- Region 4 (very large shock): $\rho > \theta(z+e)$. In that case, ρ is so large that lender wants to reject even in the best case scenario ($\theta(z+e) - \rho < 0$). Again, there is no value in learning.

This shows monitoring can only occur for intermediate values of $\rho \in [\underline{\rho}, \overline{\rho}]$. Intuitively, this range is larger if (i) monitoring costs are low, (ii) there is significant uncertainty e over terminal values ("option value of learning"). In fact, we will see that in the three-values case, the magnitude of e relative to monitoring costs ξ characterizes the equilibrium cutoffs $[\underline{\rho}, \overline{\rho}]$. To determine these cutoffs, we consider the two other regions in which monitoring is not clearly dominated.

- Region 2 (moderately small shock): $\theta(z-e) < \rho < \theta z$. In that case, lender wants to continue in all states except the worst case scenario $\epsilon = -e$. That occurs with probability q.

For a cash-flow shock of that size, the lender's optimal choice is derived as follows. If they do not monitor, their expected payoff is $\theta z - \rho$ which is positive in this region. Without monitoring, the lender thus accepts to grant funds and their expected payoff is $V^N = \theta z - \rho$. If they monitor, they will accept in all cases expect if $\epsilon = -e$. The expected payoff of monitoring is thus:

$$V^M = \underbrace{\theta z - \rho}_{V^N} + \underbrace{q[\rho - (\theta(z-e)]}_{\text{Option value}} - \underbrace{\xi}_{\text{Monitoring cost}}$$

Comparing the two implies that the lender monitors only if the shock is large enough. Intuitively, the option value of learning grows with the size of the shock ρ: low shocks are not alarming enough to justify incurring monitoring costs. Formally, that determines the lower cutoff $\underline{\rho}$:

$$V^M > V^N \iff \rho > \underline{\rho} := \theta(z-e) + \xi/q$$

A necessary condition for this monitoring solution is that $e - \xi/\theta q > 0$ (otherwise $\underline{\rho}$ is outside of Region 2). Intuitively, there must be enough uncertainty relative to monitoring costs. If this condition is violated, the lender never monitors and always accepts in this region (rubber stamping).

The analysis of the last region follows very closely the one of Region 2:

- Region 3 (moderately large shock): $\theta z < \rho < \theta(z + e)$. In that case, lender wants to continue only in the best case scenario $\epsilon = e$. That occurs with probability q.

If they do not monitor, their expected payoff is $\theta z - \rho$ which is negative in this region. Without monitoring, the lender thus reject and their expected payoff is $V^N = 0$. If they monitor, they will accept only if $\epsilon = e$. The expected payoff of monitoring is thus:

$$V^M = \underbrace{0}_{V^N} + \underbrace{q[\theta(z + e) - \rho]}_{\text{Option value}} - \underbrace{\xi}_{\text{Monitoring cost}}$$

Comparing the two implies that the lender monitors only if the shock is low enough. Intuitively, the option value of learning decreases with the size of the shock ρ: high shocks are too alarming to justify incurring monitoring costs. Formally, that determines the higher cutoff $\overline{\rho}$:

$$V^M > V^N \iff \rho < \overline{\rho} := \theta(z + e) - \xi/q$$

The condition for this monitoring solution is the same as in Region 2: $e - \xi/\theta q > 0$ (otherwise $\overline{\rho}$ is outside of Region 3). There must be enough uncertainty relative to monitoring costs. If this condition is violated, the lender never monitors and always rejects in this region (blind rejections).

Moreover, the optimal choice of committed credit lines versus giving lender discretion varies in the cross-section of firms. Note first that for some borrowers giving the lender discretion increases credit limit (on paper). To see this compare the credit limit with commitment $\hat{\rho} = \mu + \sigma h^{-1}(\frac{\mu - \theta z}{\sigma})$ and the maximum draw-down that can occur with discretion $\overline{\rho} = \theta z + (\theta e - \xi/q)$:

$$\hat{\rho} < \overline{\rho} \iff \theta e - \xi/q > \mu - \theta z + \sigma h^{-1}(\frac{\mu - \theta z}{\sigma})$$

This condition holds if uncertainty e over terminal values is sufficiently high. For these borrowers, the option value of discretion is particularly high: there is a lot to potentially learn through monitoring.

Of course, a higher credit limit on paper will not necessarily be honored when the lender has discretion. Borrower's and total surplus are determined by the probability of continuation at $t = 1$ across all realizations of (ρ, ϵ). Without discretion this probability is $F(\hat{\rho})$. With discretion, this probability is:

$$\begin{aligned} P(continuation) &= F(\underline{\rho}) + (1-q)\left[F(\theta z) - F(\underline{\rho})\right] + q\left[F(\overline{\rho}) - F(\theta z)\right] \\ &= q\left[\Phi\left(\frac{\overline{\rho}-\mu}{\sigma}\right) + \Phi\left(\frac{\underline{\rho}-\mu}{\sigma}\right)\right] + (1-2q)\Phi\left(\frac{\theta z-\mu}{\sigma}\right). \end{aligned} \tag{A.1}$$

This probability increases with uncertainty e as long as $\mu > \theta z$. In other words, the value of discretion comes from a combination of (i) uncertainty over asset values (ii) large liquidity risk relative to pleageable assets.

C.2 Policy Intervention

Ex-post subsidy: We first consider the effect of direct lending subsidy through the lens of the model. Suppose that the lender receives a transfer $s > 0$ for each loan made at $t = 1$ (equivalently, it is transferred to the borrower and is fully pleageable). It is actually straightforward to solve for the effect of this subsidy on the monitoring equilibrium at $t = 1$. Indeed, a subsidy is isomorphic to increasing expected terminal values to $\theta z + s$. The equilibrium structure is preserved: the lender monitors in a region $[\underline{\rho}(s), \overline{\rho}(s)]$ with:

$$\underline{\rho}(s) := s + \theta(z - e) + \xi/q$$

$$\overline{\rho}(s) := s + \theta(z + e) - \xi/q$$

The subsidy shifts all cutoffs to the right by s. The implications for credit are as follows: (i) there is more lending in the new equilibrium but still a lot of monitoring and rejections; (ii) the cost of raising the amount of guaranteed credit by \$1 is exactly \$1 ($\underline{\rho}(s)$ increases one-for-one with s); (iii) committed credit lines are not renegotiated upwards unless the subsidy is large enough ($s > \hat{\rho} - \theta z$).

Ex-ante subsidy: If the subsidy is put in place at $t = 0$, it now not only influence the monitoring game, but also the size of committed credit lines and the choice of borrower between the two. We have seen above how $s > 0$ changes the properties of contracts with discretion. Here we thus examine the effect of committed credit lines and then on borrower choice.

The subsidy naturally boosts committed credit lines. The borrower and lender know that they will receive s unless the firm is terminated at $t = 1$. The equilibrium condition that determines credit limit is thus amended to $\int_{-\infty}^{\hat{\rho}(s)} \theta z + s - \rho dF(\rho) = 0$, which implies that: $\hat{\rho}(s) = \mu + \sigma h^{-1}(\frac{\mu - \theta z - s}{\sigma})$. Since h^{-1} is decreasing, we can see that $\hat{\rho}(s)$ increases with the subsidy level s. Moreover, just as in the case above, one can see that a subsidy s is isomorphic to a larger level of expected terminal values $\theta z + s$.

How does the subsidy impact borrower's choice of commitment versus discretion? The subsidy tilts the trade-off toward committed credit lines, and hence can help to alleviate the effect of a large liquidity shock. To see this, recall that in laissez-faire one condition for discretion to be preferred is that terminal values are low relative to expected liquidity shock. Since the subsidy is equivalent to an increase in terminal values, it makes committed credit lines relatively more attractive.

Guarantees: In practice, loan guarantees are a common form of intervention to support lending markets. Through the lens of the model, we model a guarantee as a pair (g, f) capturing a guarantee level and a guarantee fee. Taking up the guarantee implies that the lender's payoff at $t = 2$ is at least g, at an upfront cost f. Guaranteeing the downside shares some similarity with giving a subsidy. The lender's expected payoff at $t = 2$ given the guarantee level is given by $\mathbb{E}[\max\{\theta(z + \epsilon), g\}] = \theta z + s(\theta, z, g, e, q)$, for some function $s()$ that depends on firm's characteristics.

Consider first the effect on committed credit lines. If it takes up the guarantee program, the lender's participation constraint is given by:

$$\int_{-\infty}^{\hat{\rho}(g,f)} \theta z + \underbrace{s(\theta, z, g, e, q) - f}_{\text{effective subsidy}} - \rho dF(\rho) = 0$$

This expression makes clear the first two effects of the guarantee program: (i) There is selective take-up: only firms for which the protection from downside risk out weights the fee choose to participate. For a given fee f this favor participation from riskier firms with more downside, differently from the subsidy that would be taken up by all firms. (ii) There is an expected fiscal cost of the program: indeed only firms for which there is an effective subsidy $s(\theta, z, g, e, q) - f > 0$ participate. This is because pleageability constraints θ and lenders' participation constraints still have to hold. This cost is a general feature of models of public interventions with voluntary participation (Tirole, 2012; Philippon and Skreta, 2012; Philippon and Schnabl, 2013). On a loan-by-loan basis, the public sector loses money, which can in principle be justified by the externalities of liquidation on other parts of the economy.

Guarantees also impacts contracts with discretion. Intuitively, the guarantee removes the downside which in turn reduces the option value of learning. This makes monitoring and discretion less appealing. This has two effects, depending if the program is introduced ex-post ($t = 1$) or ex-ante ($t = 0$) for the firms. Ex-post, the guarantees increases the incentives to "rubber stamp" requests for funds that are not too large, because there less downside to learn about and protect from. Larger requests still trigger monitoring, unless the guarantee level is very high: there is an intuitive trade-off between credit volume and fiscal cost. Ex-ante, guarantees tend to favor committed credit lines over discretion.

Participation/loan purchases: In this simple framework, participation by the public sector in loans (or loan purchases) does not play any role. There is no constraint on the size of lender's lending portfolios and all payoff are linear in quantities. To capture the effect of participation programs, one would need to extend the model to include aggregate bank balance sheet constraints.

D Loan Terms at Regional Banks

- List of regional banks as of 2019Q4: MT, Keycorp, Huntington, PNC, Fifth Third, SunTrust, BBT (now: Truist), US Bancorp, Citizens, Ally, Cap One, Regions

A.14-A.17 shows that our facts about loan terms hold for these regional banks as well: small firms have shorter maturity credit lines, engage in less maturity management, pledge more collateral and pay higher spreads. The magnitudes of differences across firms size are at least as large as in the full sample. In fact, they may offer harsher terms: for instance, 49% of small SMEs credit lines are demandable, while this fraction is only 29% in the whole sample. The main difference between regional banks and the larger universal banks is in the sets of firms they lend to, with regional banks tilting toward smaller borrowers relative to the univeral banks. Table A.18 shows that differences in dradowns during COVID are also equally striking for these banks: SME credit is virtually unchanged in 2020Q1, while large firms draw extensively. This additional evidence suggests that differences in loan terms and access to credit across firms we document are driven by firms characteristics rather than bank size.

Table A.14: ***Maturity at Origination/Renewal by Facility Type and Firm Size Category as of December 31, 2019 - Sample Restricted to Loans issued by Regional Banks.***

Maturity at Origination/Renewal	Demand	<1 year	1 year	1-2 year	2-4 years	4-5 years	>5 years	Obs.
Assets ($mil.)								
	Panel A: Revolving Credit Lines							
0-50	.49	.16	.17	.09	.043	.029	.013	12549
50-250	.24	.097	.08	.081	.16	.32	.033	3364
250-1000	.12	.027	.024	.048	.17	.57	.039	2271
1000-5000	.033	.014	.023	.024	.15	.73	.034	2369
5000-	.027	.039	.069	.037	.12	.68	.02	1717
	Panel B: Term Loans							
0-50	.0026	.045	.034	.02	.071	.32	.51	5760
50-250	.0017	.045	.031	.022	.14	.43	.33	2867
250-1000	.0006	.028	.018	.037	.14	.46	.31	1669
1000-5000	0	.034	.019	.042	.18	.55	.17	1187
5000-	0	.1	.072	.089	.24	.37	.12	844

Notes: The table reports the fraction of outstanding loans to each firm size group (assets in $million) by the maturity indicated in the table header. The maturity is as of the respective facility's origination date or alternatively the most recent renewal date if the facility has been renewed since origination. The sample includes all C&I loans in the Y-14 corporate loan schedule as of December 31, 2019 for which an origination or renewal date reported.

Table A.15: ***Maturity Management in Revolving Credit Lines and Term Loan by Firm Size Category- Sample Restricted to Loans issued by Regional Banks.***

Assets ($mil.)												
Original Maturity	1 year or less			1-2 years			2-4 years			more than 4		
	Before	After	N	Before	After	N	Before	After	N	Before	After	N
						Panel A: Credit Lines						
0-50	0	12	86541	2	20	18263	4	34	9813	50	60	7294
50-250	0	11	17193	6	20	7585	13	34	13113	39	57	18349
250-1000	0	12	3693	9	22	3013	21	35	11172	35	60	23230
1000-5000	0	12	2442	7	16	2406	25	36	15546	37	60	35434
5000-	0	12	4336	6	17	1869	24	37	10567	41	60	29015
						Panel B: Term Loans						
0-50	0	4	7648	0	18	3483	14	36	14070	25	63	64338
50-250	0	3	3816	3	19	2515	16	36	12884	41	60	39571
250-1000	0	6	1266	13	19	1209	25	36	6664	41	58	21751
1000-5000	0	5.5	1005	2	21	991	22	36	6427	39	60	16210
5000-	-1	2	2663	10	24	1461	24	36	5365	40	60	8889

Notes: The table reports the median maturity (in months) before and after a credit facility is renewed. Facilities are grouped by their maturity at origination/recent renewal date as noted in the header. Demand loans are excluded from the sample. The sample is restricted to all renewals of revolving credit lines (Panel A) and term loans (Panel B) reported between 2015Q1 through 2019Q4.

Table A.16: ***Collateral Use by Facility Type and Firm Size Category as of December 31, 2019- Sample Restricted to Loans issued by Regional Banks.***

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets ($mil.)								
Panel A1: Revolving Credit Lines (Non-Demand Loans)								
0-50	.028	.014	.61	.041	.094	.18	.041	10925
50-250	.035	.035	.49	.056	.11	.19	.083	3691
250-1000	.02	.083	.39	.041	.12	.2	.14	2801
1000-5000	.01	.073	.36	.039	.12	.12	.29	3368
5000-	.0028	.04	.16	.021	.083	.046	.65	2460
Panel A2: Revolving Credit Lines (Demand Loans)								
0-50	.0048	.0058	.7	.041	.024	.17	.058	7969
50-250	.0041	.017	.35	.16	.04	.12	.31	1464
250-1000	.0014	.015	.17	.16	.021	.034	.6	727
1000-5000	0	.028	.088	.011	.021	.028	.83	566
5000-	0	.007	.038	.007	.007	.019	.92	426
Panel B: Term Loans								
0-50	.47	.0059	.19	.14	.036	.11	.035	9542
50-250	.25	.02	.17	.28	.056	.19	.029	4087
250-1000	.13	.048	.13	.35	.064	.23	.055	2160
1000-5000	.059	.053	.17	.21	.1	.19	.22	1467
5000-	.024	.032	.12	.3	.095	.076	.36	1054

Notes: The table reports the fraction of loan commitments to each firm size group (by assets in $million) with the type of collateral indicated in the table header. The sample includes all loans in the Y-14 corporate loan schedule as of Deember 31, 2019.

Table A.17: ***Pricing of Revolving Credit Lines and Term Loans by Firm Size Category- Sample Restricted to Loans issued by Regional Banks.***

Dependent variable	Interest Rate (in bp)						
Sample	Credit Lines				Term Loans		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
50-250 (in mil)	-69.8***	-25.5***	-29.4***	-29.6***	-11.0***	-5.5*	0.4
	(4.2)	(2.9)	(3.0)	(3.0)	(3.3)	(2.4)	(2.4)
250-1000	-73.6***	-27.8***	-35.8***	-35.6***	-7.3	2.0	7.7
	(6.4)	(4.5)	(5.1)	(5.1)	(5.6)	(4.1)	(4.1)
1000-5000	-75.6***	-63.3***	-71.9***	-71.4***	-69.1***	-47.0***	-34.9***
	(4.0)	(4.0)	(5.0)	(5.0)	(4.8)	(3.9)	(4.0)
5000-	-116.0***	-79.6***	-83.3***	-83.2***	-104.4***	-69.5***	-55.3***
	(4.9)	(6.0)	(7.1)	(7.1)	(6.3)	(4.7)	(4.8)
Reference-Rate-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Bank-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Rating-Time FE	No	Yes	Yes	Yes	No	Yes	Yes
Firm Financial Controls	No	Yes	Yes	Yes	No	Yes	Yes
Loan Terms Controls	No	No	Yes	Yes	No	No	Yes
Drawdown	No	No	No	Yes	No	No	Yes
No of Firms	19088	16483	16452	16452	13995	11920	11887
N	56499	46858	46723	46723	25310	22121	21817
R^2	0.314	0.558	0.564	0.565	0.270	0.556	0.579

Notes: Results from estimating a model of the following type: $\text{Interest}_{\ell,t} = \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \mathbb{I}\{\text{size class} = s\} + \Gamma' X_t + \epsilon_{\ell,t}$ where $\text{Interest}_{\ell,i,b,t}$ is the interest on facility ℓ from bank b to firm i at time t. The sample contains originations and renewals between 2015Q1 and 2019Q4. Industry×time fixed effects are at the NAICS 3 digit level. Rating×time fixed effects are categorical variables for 10 internal loan rating categories. Firm financial controls are lagged debt/assets, cash and receivables/assets, net income/assets, and operating income/interest expense. Loan term controls are six maturity categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years), six collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien), and total credit line commitment over total assets. Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.18: ***Aggregate Drawdowns in $B by Firm Type, 2019Q4-2020Q2- Sample Restricted to Loans issued by Regional Banks.***

	Total Credit			Term Loans			CL Drawdowns (all facilities)			CL Drawdowns (pre-existing facilities)		
	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2
Panel A: By Firm Size (in Assets in $mil)												
Not classified	41.4	43.0	43.9	19.9	20.6	21.4	11.7	12.8	12.0	10.3	11.7	10.1
0-50	92.5	93.0	76.4	29.4	29.6	29.4	54.6	54.7	37.9	53.0	53.6	36.6
50-250	81.0	83.7	73.2	28.4	28.8	26.4	39.6	42.2	33.0	38.6	41.4	32.0
250-1000	73.3	83.8	74.5	22.8	23.9	20.4	40.0	49.3	41.4	38.5	48.2	40.0
1000-5000	95.0	120.8	104.9	28.5	30.5	26.4	48.0	71.5	58.0	47.5	71.1	57.0
5000-	74.0	105.6	87.6	24.7	28.9	26.2	26.5	52.8	36.4	26.0	52.6	34.8
	457.3	529.9	460.4	153.7	162.3	150.0	220.4	283.3	218.7	213.9	278.5	210.6

Notes: The table reports the total dollar amount (in $B) of utilized credit pooling all facilities, revolving credit lines only, and revolving credit lines of firms that had a facility open as of the previous quarter.

E Private vs. Public Firms

Table A.19: ***Remaining Maturity by Facility Type and Firm Size Category for Loans Outstanding between 2017Q1-2019Q4***

Loan Due:	Demand	Jan	Feb	Mar	Q2	Q3-Q4	2021	2022-24	Later	Obs.
Assets (mil.)										
Panel A1: Revolving Credit Lines for Private Firms										
0-50	.29	.042	.046	.051	.17	.23	.11	.04	.023	429262
50-250	.18	.022	.024	.028	.082	.15	.18	.22	.12	124015
250-1000	.13	.0086	.0093	.012	.038	.084	.15	.35	.23	68935
1000-5000	.096	.0049	.006	.0075	.023	.054	.13	.42	.29	40876
5000-	.097	.012	.0094	.013	.033	.075	.12	.37	.29	16832
Panel A2: Revolving Credit Lines for Public Firms										
0-50	0	.038	.05	.059	.15	.25	.13	.059	.031	8774
50-250	0	.011	.014	.014	.044	.096	.18	.35	.2	6416
250-1000	0	.0025	.0039	.0047	.015	.039	.13	.44	.32	24182
1000-5000	0	.0017	.0017	.003	.009	.025	.11	.47	.33	68519
5000-	0	.0072	.0074	.0083	.021	.046	.1	.42	.36	86389
Panel B1: Term Loans for Private Firms										
0-50	.0015	.006	.0062	.0079	.018	.036	.068	.22	.65	262199
50-250	.0013	.0064	.0059	.0077	.02	.044	.11	.36	.46	100486
250-1000	.0015	.0045	.0047	.007	.016	.043	.13	.38	.43	42007
1000-5000	.000061	.0034	.0068	.008	.021	.05	.11	.35	.47	16371
5000-	0	.0056	.0085	.013	.037	.08	.15	.35	.38	6205
Panel B2: Term Loans for Public Firms										
0-50	0	.0052	.0069	.011	.019	.038	.075	.23	.62	5199
50-250	0	.0043	.0074	.0045	.013	.029	.095	.41	.45	4217
250-1000	0	.002	.0017	.0043	.009	.028	.11	.42	.44	7522
1000-5000	0	.0029	.0026	.0035	.0096	.029	.11	.47	.4	22570
5000-	0	.019	.012	.013	.034	.076	.14	.39	.33	24349

Notes: The table reports the fraction of loans to each firm size group (assets in $milion) with remaining maturity indicated in the table header. The sample includes all C&I loans in the Y-14 corporate loan schedule reported as outstanding between 2017Q1 and 2019Q4

Table A.20: ***Collateral Use by Facility Type and Firm Size Category, 2017Q1-2019Q4***

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets (mil.)								
Panel A1: Revolving Credit Lines for Private Firms								
0-50	.023	.015	.46	.034	.046	.39	.042	306703
50-250	.027	.025	.45	.059	.075	.27	.096	101954
250-1000	.018	.038	.37	.054	.11	.23	.18	60042
1000-5000	.0091	.036	.33	.043	.11	.17	.3	36949
5000-	.0025	.019	.13	.016	.075	.077	.68	15191
Panel A2: Revolving Credit Lines for Public Firms								
0-50	.018	.022	.44	.031	.045	.41	.043	6803
50-250	.012	.028	.44	.065	.077	.28	.1	5796
250-1000	.0035	.045	.39	.047	.097	.26	.16	22374
1000-5000	.0029	.045	.3	.041	.1	.18	.33	63763
5000-	.00092	.021	.098	.02	.072	.072	.72	81466
Panel B1: Term Loans for Private Firms								
0-50	.5	.0063	.1	.11	.023	.25	.022	261812
50-250	.25	.013	.13	.29	.044	.23	.035	100353
250-1000	.17	.027	.13	.33	.053	.21	.073	41942
1000-5000	.15	.025	.12	.25	.088	.19	.19	16370
5000-	.049	.0087	.049	.27	.077	.12	.43	6205
Panel B2: Term Loans for Public Firms								
0-50	.46	.0054	.081	.11	.021	.29	.032	5191
50-250	.17	.02	.17	.23	.059	.3	.061	4215
250-1000	.02	.04	.23	.2	.083	.33	.11	7520
1000-5000	.015	.041	.19	.12	.081	.23	.32	22568
5000-	.0082	.025	.11	.15	.07	.15	.49	24347

Notes: The table reports the fraction of loan commitments to each firm size group with the type of collateral indicated in the table header. The sample includes all loans in the Y-14 corporate loan schedule as of 2019Q4.

Table A.21: ***Interest Rates by Facility Type and Firm Size Category between 2017Q1-2019Q4***

Interest in bp	0 -100	100-200	200-300	300-400	400 -500	500 -600	>600	Obs.
Assets (mil.)								
Panel A1: Revolving Credit Lines for Private Firms								
0-50	.019	.011	.065	.25	.37	.22	.062	294042
50-250	.045	.035	.16	.35	.23	.1	.083	86557
250-1000	.061	.039	.15	.32	.22	.12	.1	50562
1000-5000	.074	.017	.18	.33	.22	.11	.078	34843
5000-	.17	.054	.23	.32	.13	.057	.047	12297
Panel A2: Revolving Credit Lines for Public Firms								
0-50	.036	.0049	.064	.28	.35	.16	.1	609
50-250	.062	.0077	.11	.29	.24	.14	.15	2352
250-1000	.072	.0093	.13	.33	.24	.12	.099	11769
1000-5000	.083	.028	.2	.38	.18	.063	.056	32005
5000-	.18	.046	.22	.36	.11	.049	.042	20926
Panel B1: Term Loans for Private Firms								
0-50	.015	.0039	.063	.33	.44	.12	.027	267099
50-250	.021	.0084	.14	.38	.3	.088	.058	103035
250-1000	.032	.015	.17	.37	.24	.083	.081	44211
1000-5000	.044	.015	.21	.41	.21	.064	.047	20943
5000-	.068	.031	.25	.42	.18	.031	.019	11818
Panel B2: Term Loans for Public Firms								
0-50	.053	0	.11	.24	.34	.16	.099	282
50-250	.024	.014	.099	.28	.26	.21	.12	1631
250-1000	.061	.0078	.1	.33	.3	.12	.082	5232
1000-5000	.052	.023	.21	.45	.2	.037	.024	17995
5000-	.1	.033	.27	.42	.13	.035	.015	18733

Notes: The table reports the fraction of loan commitments to each firm size group with the interest rate indicated in the table header. Note that prices for credit lines are only reported if the drawdown is larger than zero. The sample includes all loans in the Y-14 corporate loan schedule as of 2019Q4.