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Bank liquidity provision across the firm size distribution[☆]

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ABSTRACT

We use supervisory loan-level data to document that small firms (SMEs) obtain shorter maturity credit lines than large firms, 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. Consistent with this hypothesis, SMEs did not draw down whereas large firms did, even in response to similar demand shocks. PPP recipients reduced non-PPP loan balances, indicating the program bolstered their liquidity and alleviated the shortfall.

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 su-

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[1] See, e.g., “Much of America Is Shut Out of The Greatest Borrowing Binge Ever,” August 13, 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).

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pervisory data covering 60% of all corporate loans, including loans to 50,000 SMEs, we present four facts about differences in loan terms that reflect that credit to large firms is more *committed* relative to small firms, for which the lender has substantial *discretion* in granting funds. Relative to large firms, small firms (i) obtain credit lines more frequently demandable or with much shorter maturity, (ii) post more collateral, (iii) have higher utilization rates, and (iv) 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 precommitted 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' drawdown rates exhibited a higher sensitivity to industry-level measures of exposure to the COVID recession. Rather than demand, differences in drawdowns appear to reflect 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.

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 includes 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 articulate 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 pledgeable 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 may appear available. Both types of contracts reduce credit constraints: commitment does so through an insurance channel by cross-subsidizing high and low shocks, and discretion does so 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 a 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 is more valuable when the option value of monitoring is larger. We show that smaller firms tend to have higher volatility and less frequently audited financials, giving the prediction that discretion is more likely in lending to smaller firms.

Section 4 presents the four facts about bank loan terms and firm size. Fact 1 documents sharp differences in rates of expiring or near-expiring credit lines. Among firms with less than $50 million in assets, 30% of credit lines take the form of demand loans that are immediately callable by the lender. These demand loans epitomize the idea of discretion: they are by definition not committed. More generally, three-quarters of loans to these firms have maturity at origination of one year or less. Small firms do not actively manage maturity on their short-term credit lines, leaving 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. The frequent expiration of credit lines to small firms gives lenders the threat point to not roll over in negotiating with borrowers who want to draw funds; in the limiting case of demand loans, any time the borrower requests funds, the lender can monitor and reject. The share of credit lines with less than one-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 five-year facility. The median renewal on this facility occurs with more than three years of maturity remaining, such that only 15% of credit lines to the largest firms had less than one year of maturity remaining at the end of 2019 and the median loan had around three years of maturity remaining. The maturity difference does not manifest for term loans, for which the vast majority of credit to both small and large firms originates with five or more years of maturity and typically renews well before maturity. In our framework, term loans offer little scope for discretion since the bank disburses the funds up front.

Fact 2 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). The share unsecured increases with firm size; 70% of credit lines to firms with more than $5 billion in assets are unsecured. As well, small firms' drawdowns are more sensitive to collateral values. 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. Importantly, cross-sectional differences in maturity and collateral line up with underlying borrower characteristics, such as the quality of financials and firm risk.

Fact 3 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 suggests that in normal times contracts with discretion mostly allow small firms to access liquidity when needed. However, SMEs draw less around idiosyncratic distress events: large firms increase utilization in the quarters preceding a downgrade or default, while smaller firms see much more muted change. This evidence illustrates our main trade-off: discretionary loan terms let small firms access more credit in normal times, but restrict the flow of new credit after bad news.

Fact 4 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 that provide the lender 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 drawdowns on 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 is robust to 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 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, cash holdings, and bond market access help to alleviate this concern by removing the possibility of large firms operating in more severely impacted industries or states, having less cash on hand, or having used their credit lines 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 code between 2019Q2 and 2020Q2 less the trailing five-year change. This measure is available for all firms and lines up fairly well with health-related risks. 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 also confirm, using Compustat data, that our main measure correlates strongly with changes in revenue, and 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 drawdowns only emerges 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 the 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 firms that have fewer than 500 employees or that satisfy certain other eligibility criteria, and made these loans forgivable if the borrower kept its 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 80% 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 in a sample that includes much smaller firms than appear in the syndicated market. In recent work, Lian and Ma (2021) 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. Our data also highlight the prominence of demand loans for small firms. Berg et al. (2021) 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 microenterprises 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) document the sharp increase in bank credit outstanding in 2020Q1 and show 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) conjecture 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. Other studies on bank lending in 2020 include Berger et al. (2020), Kapan and Minoiu (2020), and Beck and Keil (2020).

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., 2021; Koetter 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, Forthcoming; Ippolito et al., 2019; Murfin, 2012). We broaden this discussion 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 led to an extraordinarily 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 (see also Nikolov et al., 2019). Other works have studied aggregate liquidity constraints when the banking sector might not be able to honor all credit line drawdowns (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 preexisting 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

[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; Smith Jr and Warner (1979); Aghion and Bolton (1992); Berlin and Mester (1992); Garleanu and Zwiebel (2009); Attar et al. (2019); Griffin et al. (2019); Berlin et al. (2020); Davydenko et al. (2020); Greenwald (2019); Drechsel (2020) on covenants; and work studying combinations of loan terms in Hart and Moore (1994); Rajan and Winton (1995); Park (2000); Donaldson et al. (2019); Kermani and Ma (2020).

[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.

the committed amount, 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 repricing 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 4686 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 to 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 million and $250 million in assets, 4830 firms with between $250 million and $1 billion in assets, 3176 firms with between $1 billion and $5 billion, and 2412 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 contains 1004 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.

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.

[4] We identify 3328 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 3328 firms, we are able to identify 2135 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.

[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.

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	4830
1000 – 5000	1.0	2.4	300.4	43.9	894.8	2,835.0	3176
5000–	1.0	2.2	612.4	44.0	1,861.5	6,607.5	2412
Panel B: Compustat							
0–50	1.0	1.0	5.6	2.7	13.3	32.2	1004
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	1145
5000–	1.2	4.7	981.4	215.5	2,918.0	7,611.8	1109
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.

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 that 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. 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 ρ. For tractability, we assume full support $\rho \sim \mathcal{N}(\mu, \sigma^2)$, 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

[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.

[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

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 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 that no new investment opportunities arrive at $t=0$ that could absorb financing. Incomplete pledgeability 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 versus 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. Importantly, the credit limit is higher than the expected pledgeable value: $\hat{\rho}>\theta z$.[9] 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.[10] 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 to observe the shock ϵ; and (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.[11]

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 monitoring, respectively. Without monitoring, the lender agrees to lend only when ρ is less than the expected pledgeable value θz, and its payoff is thus $V^N=\max\{\theta z-\rho,0\}$. The value of monitoring comes 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 $\int_{\theta\epsilon>\overline{\rho}-\theta z}\theta(z+\epsilon)-\overline{\rho}\quad dG(\epsilon)=\xi$.[12] The left panel of Fig. 1 illustrates the monitoring decision graphically.

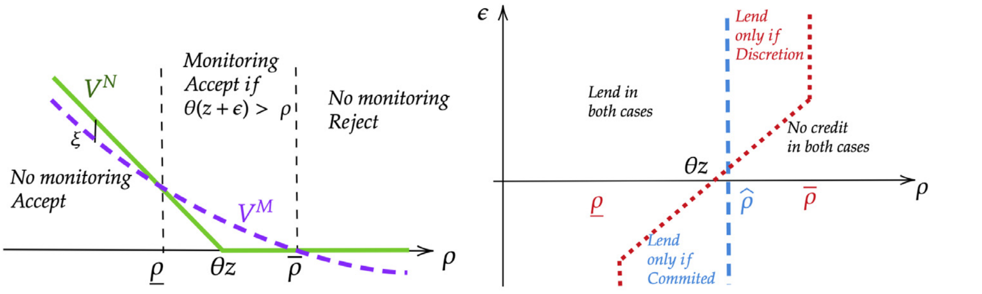
agnostic on the exact source of the cash-flow shock: it can capture a fall in internal funds or a precautionary motive. Since our focus is on credit line design and use, we do not explicitly model other aspects of corporate liquidity management, such as cash balances, equity issuance, or (dis)investment, 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). To economize on notation, we also assume that positive cash-flow shocks at $t=1$ can be paid out in full to the lender at $t=2$.

[9] To obtain the expression for $\hat{\rho}$, rewrite the participation constraint as $\mathbb{E}[\rho|\rho<\hat{\rho}]=\theta z$ and use the property that the mean of the truncated normal distribution of $F(\rho)$ over $[-\infty,\hat{\rho}]$ is $\mathbb{E}[\rho|\rho<\hat{\rho}]=\mu-\sigma h\left(\frac{\hat{\rho}-\mu}{\sigma}\right)$. The result $\hat{\rho}>\theta z$ follows because $h(x)>-x\ \forall x$.

[10] Note, however, that not all terminations are inefficient: if ϵ is large and negative, continuation has negative NPV. The value of discretion in preventing "excessive continuation" is part of the trade-off we emphasize below.

[11] 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 (such as 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. For simplicity, our framework does not account for moral hazard at $t=1$, which would increase the value of discretion.

[12] 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 sub-



(a) Monitoring Region With Discretion (b) Lending Under Discretion Versus Commitment

Fig. 1. Model properties.

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 types 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) is less valuable when very large cash-flow shocks are more likely, and discretion is 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.[13] 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 pledgeable 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 their 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).[14] 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).[15] 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 that shows that smaller firms tend to be riskier, more opaque, and thus ultimately more constrained (Gertler and Gilchrist, 1994; Petersen and Rajan,

tracts the monitoring cost ξ. The expected value of not monitoring given $\rho < \theta z$ is simply $\theta z - \rho$. The expression defining $\overline{\rho}$ is analogous except that when $\rho = \overline{\rho}$ the value of not monitoring is zero.

[13] 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 hand, large firms have greater complexity per unit of assets, implying a convex cost of monitoring.

[14] 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 credits are adjusted each quarter, and that opaque borrowers are more proactively monitored.

[15] 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 them in the direction of discretion. Calvino et al. (2018) show using business register data covering 20 countries that smaller firms have more volatile employment growth 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	0.96	0.4	3.2	0.27	0.065	4.8	622,257
50–250	0.96	0.48	2.9	0.68	0.17	4.3	212,128
250–1000	0.93	0.47	2.9	0.82	0.25	3.9	146,600
1000–5000	0.93	0.53	2.6	0.88	0.35	3.4	170,367
5000–	0.93	0.59	2.5	0.9	0.41	3.1	163,265

Notes: The table summarizes the frequency with which the date of financials (or audited financials) is 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.

1994; Berger and Udell, 2006; Whited and Wu, 2006; Hennessy and Whited, 2007). This literature has also emphasized 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 solely 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 a quarterly frequency, which may explain why contracts to small firms do not rely solely on covenants.[16] 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.

This idea of short maturity or collateral giving lenders de facto control rights is central to the financial contracting theory literature. For instance, Rajan and Winton (1995) show that short-term debt gives lenders incentives to monitor and liquidate efficiently, and that for smaller, less well-known firms, short-term debt can dominate long-term debt with covenants (since the latter needs to be based on verifiable information, while a "short-term loan gives the bank unlimited power to act"). Kermani and Ma (2020) argue that collateral shapes contracting and control rights beyond liquidation values and that different types of collateral lead to different control rights: "A key economic function of blanket liens is to implement strong control over the company," while other types of "harder" collateral give rise to asset-based debt with weak control. Such loan terms may restrict the firm's *effective* ability to access liquidity even if they do not *explicitly* prevent drawdowns. For example, a firm with a five-year credit line can draw and not repay for another eighteen months if it so chooses. A firm with a one-year credit line can do so as well, but only if the lender agrees to roll over the line at maturity. Importantly, while the lender might not be able to explicitly prevent the drawdown, the necessity to roll-over effectively gives it some control and influence over the firm's decision of how much and when to draw.

We summarize this section with three predictions. First, small firms have loan terms that reflect discretion relative to those of large firms. Their credit lines are more likely to be demandable or have short maturity such that they must be rolled over frequently. In addition, small firms' lines have higher collateral requirements.

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 $\rho \in [\underline{\rho}, \overline{\rho}]$, 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.[17] We emphasize this is a *relative* prediction; in reality,

[16] 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.

[17] 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

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 the PPP. Programs that stimulate credit over and above the market allocation are likely to carry an element of subsidy. The reason for this 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 they relaxed pledgeability or participation constraints, private parties would have already incorporated them.[18] 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 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 four 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 replicates them in the subset of Compustat-matched borrowers.

Fact 1: Small firms have short-term credit lines while large firms have long-term credit lines. Other loan types have similar maturity across the size distribution. Because small firms do not actively manage maturity of short-term loans, they frequently have expiring credit lines.

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 the sample 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. The fact that demand loans are so common for small firms while being virtually nonexistent for large firms is direct evidence of differences in lender discretion across the size distribution, in line with our theoretical predictions.

An additional 23% of loans to these SMEs have maturity of less than one year and another 23% have 364-day credit lines, so three-quarters of credit lines to small SMEs have one year or less of maturity at origination. Less than 10% of credit lines to these firms originate with more than two 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 two or more years of maturity at origination, and two-thirds of credit lines to these firms have more than one 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 two years and three-quarters have maturity of greater than four years, with the modal credit line a five-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 two years, and the majority of term loans have original maturity of greater than four 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.

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 and even reverse for the longest maturity credit lines, 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 (two to four year) term loans well in advance of expiration. However, as shown in Table 3, most term loans to both small and large firms have more than four years of maturity at origination. Across the size distribution, the median renewal on these loans occurs with around four years of maturity remaining.

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.

[18] 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. First, 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. This is less likely to be the case when banks have strong balance sheets and low cost of funds. Second, if the government is a more efficient lender than the banking sector.

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	0.29	0.23	0.23	0.16	0.058	0.028	0.013	26,924
50–250	0.15	0.12	0.1	0.15	0.19	0.28	0.03	8089
250–1000	0.076	0.046	0.04	0.066	0.17	0.56	0.045	5924
1000–5000	0.024	0.021	0.021	0.033	0.15	0.71	0.047	6598
5000–	0.018	0.039	0.059	0.042	0.12	0.67	0.048	6199
Panel B: Term Loans								
0–50	0.0012	0.041	0.022	0.015	0.07	0.26	0.59	13,612
50–250	0.0013	0.04	0.022	0.024	0.14	0.43	0.34	6222
250–1000	0.00061	0.032	0.014	0.034	0.13	0.48	0.31	3293
1000–5000	0	0.037	0.017	0.033	0.16	0.53	0.22	2587
5000–	0.0005	0.071	0.048	0.087	0.25	0.38	0.16	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.

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	17,679
50–250	0	12	48580	6	21	29236	12	34	38101	38	60	44,975
250–1000	0	12	12913	9	22	10501	21	35	34285	36	60	68,380
1000–5000	0	12	7626	11	19	7188	26	36	43873	38	60	106,056
5000–	1	12	14996	12	20	7116	28	36	36860	44	60	106,849
Panel B: Term Loans												
0–50	0	4	17670	2	18	6975	19	35	30932	47	69	162,379
50–250	0	6	8034	6	16	5577	23	33	29441	42	60	95,464
250–1000	0	9	3028	12	18	2654	25	33	16214	43	59	50,240
1000–5000	1	11	2637	10	20	2142	26	33	14869	45	59	41,947
5000–	1	7	5221	12	18	3893	29	34	14902	48	59	27,810

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.

Since the largest firms have primarily long-term credit lines and term loans, 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 (Forthcoming). 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, these results describe one way that lenders maintain discretion over precommitted credit to small firms: they lend at short maturity, which requires more frequent rollover decisions. More frequent rollover decisions for small firms in turn give the lender greater opportunity to adjust loan terms or withdraw credit.

Fact 2: 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), 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

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	0.28	0.029	0.029	0.032	0.19	0.27	0.1	0.055	0.0089	37,067
50–250	0.19	0.016	0.014	0.018	0.081	0.15	0.17	0.33	0.015	10,901
250–1000	0.13	0.0034	0.0038	0.0039	0.039	0.074	0.13	0.59	0.016	8142
1000–5000	0.096	0.0023	0.0026	0.0017	0.018	0.041	0.1	0.72	0.0099	9503
5000–	0.078	0.0069	0.0059	0.0068	0.022	0.053	0.092	0.72	0.014	8662
Panel B: Term Loans										
0–50	0.0015	0.0043	0.0056	0.0063	0.018	0.036	0.063	0.36	0.5	22,541
50–250	0.0015	0.0057	0.0058	0.0076	0.02	0.042	0.12	0.55	0.24	8830
250–1000	0.0011	0.0025	0.0034	0.0062	0.019	0.041	0.11	0.62	0.2	4387
1000–5000	0	0.0054	0.0027	0.0072	0.019	0.04	0.097	0.68	0.14	3333
5000–	0.00038	0.014	0.011	0.01	0.04	0.082	0.14	0.58	0.12	2598

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

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	0.023	0.015	0.47	0.029	0.049	0.38	0.037	26762
50–250	0.025	0.026	0.44	0.057	0.083	0.28	0.092	8792
250–1000	0.015	0.043	0.37	0.048	0.11	0.25	0.17	7073
1000–5000	0.0054	0.038	0.31	0.039	0.11	0.18	0.32	8586
5000–	0.0019	0.018	0.1	0.015	0.074	0.074	0.71	7987
Panel A2: Revolving Credit Lines (Demand Loans)								
0–50	0.0077	0.012	0.66	0.034	0.049	0.16	0.079	10942
50–250	0.0055	0.026	0.37	0.084	0.037	0.11	0.37	2901
250–1000	0.0017	0.02	0.18	0.069	0.018	0.058	0.65	1773
1000–5000	0.0007	0.022	0.11	0.0056	0.012	0.046	0.81	1423
5000–	0	0.015	0.053	0.0041	0.02	0.026	0.88	984
Panel B: Term Loans								
0–50	0.48	0.0044	0.11	0.12	0.025	0.25	0.019	22508
50–250	0.24	0.012	0.13	0.31	0.043	0.23	0.026	8817
250–1000	0.14	0.027	0.13	0.35	0.056	0.24	0.063	4382
1000–5000	0.074	0.028	0.14	0.18	0.086	0.23	0.26	3333
5000–	0.02	0.018	0.082	0.23	0.068	0.15	0.44	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.

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. Kermani and Ma (2020) discuss how collateral shapes contracting and control rights beyond liquidation values.

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 that is 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 billion 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, as 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 billion 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 are the typical security for larger firms.

Appendix Table A.4 documents differences in collateral posting across industries; for example, firms in the retail

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%	|Δ Util./ Comm. % |	Obs.
0–50	0.33	0.087	0.12	0.15	0.14	0.17	10	36,827
50–250	0.35	0.1	0.12	0.15	0.14	0.14	9.4	10,928
250–1000	0.37	0.12	0.14	0.15	0.12	0.094	8.4	8122
1000–5000	0.47	0.16	0.13	0.11	0.075	0.067	7.7	9447
>5000	0.77	0.08	0.053	0.03	0.014	0.056	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.

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 in Table A.5 in the Appendix.

The reliance of small firms on collateralized credit facilities suggests that their access to liquidity is more sensitive to 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). The sensitivity of utilization to collateral values is: i) roughly twice as large for small SMEs as for large firms; ii) greatest for facilities backed by AR&I and (albeit noisily) real estate; and 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.

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 3: In normal times, small firms have higher, more volatile utilization of credit lines, but draw less around idiosyncratic distress events

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 penultimate 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., 2021; Greenwald et al., 2020).[19]

While small firms have higher unconditional drawdown rates, they increase utilization by less than large firms in periods of idiosyncratic distress. Fig. 2 shows mean utilization rates in the quarters preceding a downgrade of the firm's internal risk rating (Panel (a)) and preceding a default (Panel (b)), pooling over the period 2015q1 to 2020q2. Large firms increase utilization in the quarters preceding a downgrade or a default, while smaller firms see little to no change. This evidence illustrates the main trade-off of the framework above: discretionary loan terms let small firms access more credit in normal times, but restrict the flow of new credit after bad news. The next section studies the COVID period to provide evidence of divergent trends in utilization rates across small and large firms during an aggregate shock.

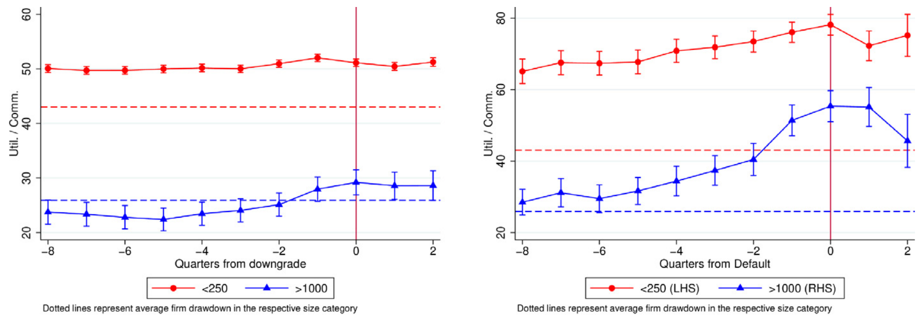
Fact 4: Small firms pay higher spreads, even conditional on observable firm and bank characteristics

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 interpret 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 first order stochastically dominates the distribution for the second smallest size class, and so on up to the largest firms, which 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×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 on a loan 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 effects. Including all of these observable firm character-

[19] Prior 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 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.



(a) Drawdowns Prior to Downgrade. (b) Drawdowns Prior to Default.

Fig. 2. Drawdowns prior to downgrade/default by firm size. Data are restricted to a balanced panel of loans where utilization is observed for all eight quarters prior to and including downgrade or default. The balanced panel restriction is not applied to quarters after the downgrade or default occurs, and those quarters are depicted in this graph for illustrative purposes. Downgrade is measured at the loan-level. Default is defined as a firm being placed on non-accrual. Confidence intervals for the mean drawdown by firm size based on robust standard errors and were estimated as in Cattaneo et al. (2019).

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	0.015	0.01	0.054	0.3	0.41	0.17	0.04	24293
50–250	0.048	0.03	0.16	0.4	0.2	0.076	0.083	7392
250–1000	0.068	0.026	0.16	0.34	0.22	0.091	0.1	5489
1000–5000	0.086	0.017	0.21	0.37	0.16	0.078	0.075	5817
5000–	0.2	0.02	0.24	0.32	0.11	0.053	0.053	2623
Panel B: Term Loans								
0–50	0.015	0.0018	0.029	0.38	0.42	0.13	0.026	22541
50–250	0.024	0.0031	0.074	0.49	0.28	0.079	0.054	8826
250–1000	0.026	0.0059	0.11	0.47	0.24	0.076	0.07	4386
1000–5000	0.035	0.011	0.2	0.54	0.13	0.045	0.036	3333
5000–	0.094	0.019	0.26	0.46	0.12	0.029	0.013	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.

istics 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 that small borrowers are risky beyond observable characteristics, consistent with concerns about unverifiable financial statements or other soft information known to the lender.

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.[20] Finally, Column (4) shows that differences in utilization of credit lines across small and large firms (fact 3) do not add explanatory power.[21]

Other firm characteristics

In the model in Section 3, firm size matters for loan terms insofar as small firms exhibit other characteristics such as greater uncertainty or less pledgeability of cash flows that lead to discretion. Section 3.3 provided evidence of this relationship along two dimensions, the likelihood of a firm's having audited financial statements and the volatility of a firm's revenue, earnings, and returns, as well as the firm's internal rating. A natural question is

[20] Table A.7 in the Appendix shows that market concentration cannot explain the size gradient, militating against a pure market power explanation as in Wang et al. (2020).

[21] 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 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	41,645	37,172	37,053	37,053	31,208	26,314	26,214
N	130,277	114,102	112,545	112,545	61,320	53,822	52,412
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: Interest $_{\ell,t} = \sum_{s\neq\{\$0-50m\}} \beta_{1,s}\mathbb{I}\{\text{size class} = s\} + \Gamma' X_t + \epsilon_{\ell,t}$ where 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.

whether these characteristics independently predict discretion. Tables A.14–A.19 of the online appendix shows that they do. Even within a firm size class, firms without audited financial statements are more likely to have a demand loan, and firms with higher volatility or a lower rating are more likely to post collateral. Although beyond the formal predictions of our simple model, this sorting makes sense: a lack of audited financial statements makes the value of collateral less certain and hence less valuable to the lender relative to the full discretion offered by a demand loan, while, with imperfect monitoring about terminal cash flows, collateral offers protection from residual risk above its role in granting discretion.

Summary

Frequently expiring credit lines and collateral requirements increase lenders' effective control rights over drawdowns. The Y-14 data do not provide coverage of other terms associated with discretion, such as covenant tightness or capaciousness of Material Adverse Change (MAC) clauses. Nonetheless, the bundling of terms observed in the Y-14, namely that small firms have shorter maturity credit lines *and* higher collateral requirements *and* pay higher spreads even conditional on these terms, strongly suggests complementarity across terms that grant lenders discretion and shield them from borrower risk. This complementarity leads us to expect more discretion also along the dimensions not observed in the Y-14. To assess whether the overall bundle of terms to small firms makes them less able to draw in bad times, the next section turns to the provisioning of credit to small and large firms following the COVID-19 cash-flow shock.

5. COVID and drawdowns

We now assess how these differences in loan terms influenced firms' access to liquidity in the first half of 2020. We describe unconditional differences in credit line utilization, estimate drawdown rates while controlling for firm characteristics, present evidence of heterogeneous utilization in response to the COVID shock, and, finally, 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.[22]

[22] 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

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 (leftmost 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 (rightmost 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 with the purpose to back up a commercial paper (CP) facility.

The evolution of credit outstanding overwhelmingly reflects differential drawdown rates on existing credit line facilities, as shown in the rightmost 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 credit occurred on these lines (see also Greenwald et al., 2020). The basic specification takes the form:

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

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized to 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 percentage points) 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 percentage points 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 (operating income before depreciation & amortization/assets), cash over assets, year-over-year sales growth, and categorical variables for the internal firm rating, each interacted with COVID. These controls slightly *increase* the size gradient to 9.2 percentage points, echoing our finding in fact 4 that observable firm characteristics cannot explain the drawdown gradient by

with balance sheet data reported in both 2019Q4 and 2020Q1, ruling out the possibility that unobserved debts explain these patterns. Another possibility is that small firms raised more external equity during this period. In fact, Hotchkiss et al. (2020) find that smaller publicly-traded firms issued more equity in the first half of 2020 than did larger public firms. On the other hand, most small firms in the Y-14 are not publicly traded. Using the balanced sample with balance sheet data reported, we do not find increases in book equity among these firms.

Table 11
Drawdowns by firm size.

Dependent variable	Drawdown rate (in ppt)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
50–250 (in mil) × COVID	4.1***	4.0***	3.0***	3.0***	2.2***	2.0***	4.1***	0.4	0.5**
	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.8)	(0.4)	(0.2)
250–1000 × COVID	10.5***	10.3***	8.8***	8.6***	6.7***	6.9***	8.3***	3.9***	3.6***
	(1.2)	(1.2)	(1.0)	(1.0)	(1.1)	(1.1)	(1.3)	(0.9)	(0.6)
1000–5000 × COVID	13.5***	12.6***	10.8***	10.6***	8.8***	9.1***	10.7***	5.3***	4.8***
	(1.7)	(1.6)	(1.1)	(1.1)	(1.0)	(1.1)	(1.3)	(1.1)	(0.7)
5000- × COVID	14.1***	12.6***	10.2***	9.9***	8.2***	9.2***	11.4***	5.3***	3.8***
	(2.4)	(2.1)	(1.5)	(1.5)	(1.4)	(1.5)	(1.7)	(1.5)	(1.0)
Bond Market × COVID		1.8*	1.6	1.6*	1.3	1.2	0.3	0.7	−0.0
		(1.0)	(1.0)	(0.9)	(0.8)	(0.8)	(1.0)	(0.8)	(0.7)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No	No	No	No
Bank-Time FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Financials	No	No	No	No	No	Yes	Yes	Yes	Yes
Rating-Time FE	No	No	No	No	No	Yes	Yes	Yes	Yes
Maturity Controls	No	No	No	No	No	No	No	Yes	Yes
Collateral Controls	No	No	No	No	No	No	No	Yes	Yes
Interest Rate Controls	No	No	No	No	No	No	No	No	Yes
Drawdown in 2019q4	No	No	No	No	No	No	No	No	Yes
No of Firms	62,615	62,615	62,615	62,615	62,614	56,568	15,850	56,568	41,292
N	786,188	786,188	786,188	786,186	786,156	712,177	348,522	712,113	518,256
R^2	0.83	0.83	0.83	0.83	0.83	0.83	0.82	0.84	0.86

Notes: Results from estimating a model of the following type: $\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \sum_{s\neq\{\$0-50m\}} \beta_{s,1}[\mathbb{I}\{\text{size class} = s\}] \times \text{COVID} + \Gamma' \times X_\ell \times \text{COVID} + \epsilon_{\ell,t}$, where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized to 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 three-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, operating income plus depreciation and amortization/assets, year-over-year sales growth, 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, and more than 4 years) and six collateral classes (real restate, marketable securities, accounts receivable and inventory, fixed assets, other, and unsecured or blanket lien), each interacted with COVID. Interest rate controls include interest rate spread, and an indicator variable for whether interest rate spread is reported (this only occurs for non-fixed rate credit lines with > 0% drawdown); in this specification, all fixed rate loans are dropped. Robust standard errors are clustered at the NAICS three-digit level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

firm size. It also indicates that SMEs' larger cash holdings do not explain their lower drawdown rates. We find that an even larger size gradient persists if we control for borrower financials but restrict our sample only to firms that report updated financials, as we do in column (7).

Column (8) 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% compared to column (6). Furthermore, the 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.[23] As an illustration, Figure A.2 shows that drawdowns are clearly concentrated in loans with longer maturity, and that the gradient is visible for both large and small firms. (Of course, the share of short-term/demand loans is significantly larger for smaller firms.)

Delving further, the maturity gradient is steeper for unsecured or blanket lien lines, as shown in Figure A.3. For SMEs, drawdown activity is roughly 10 percentage points 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 5 percentage points, consistent with a complementary 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. Overall, this evidence inculpates loan terms that grant discretion as a reason for lower drawdown rates by small firms. Importantly, since we do not observe all loan terms, the 40% dent in the size gradient from controlling for collateral and maturity may significantly understate the total scope for loan terms to explain the differential in drawdowns.

Finally, Table 11 column (9) additionally controls for the interest rate and the 2019Q4 utilization rate bin, each in-

[23] 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.

teracted with COVID.[24] 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.[25] Taken together, our analysis shows that SMEs faced less access to liquidity in response to the COVID recessions and that the difference appears to be at least partly explained by more restrictive maturity and collateral terms.

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.

Our main measure of cash-flow shocks 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. 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 the average Q2-to-Q2 growth rate between 2015 and 2019, reverse the sign so that a higher value signifies more exposure to the recession, and refer to the resulting measure as the abnormal employment or sales change.[26]

We first establish that abnormal employment growth correlates with actual cash-flow shocks during COVID. Table 12 reports regressions using firms in Compustat (not necessarily those also in the Y-14) of median and mean industry revenue growth during the first three quarters of 2020 relative to the first three quarters of 2019. Because the remainder of this section examines the impact of exposure on drawdowns across the firm size distribution, the table reports the relationship with the abnormal employment change separately for SMEs and large firms with more than \$1 billion in assets. For both large and small firms, a one standard deviation increase in exposure implies a roughly 15 percentage points decline in sales growth, and this effect is highly statistically significant. The data do not reject equality of the intercept or slope of revenue growth across large and small firms.

Fig. 3 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 Figure A.4 reports the corresponding plots for each of our five size categories. The figure makes clear that 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 that are 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 summarized in Table 13. 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 a one standard deviation higher industry exposure results in a 3.1 percentage point higher drawdown rate in 2020Q1.

Column (2) reports the triple-difference specification:

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

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.

Fig. 4 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 as-

[24] Including these variables shrinks the sample somewhat since interest rate spreads are not reported for fixed rate loans or loans with zero-drawdown. We have verified that the sample change alone has almost no impact on the coefficients.

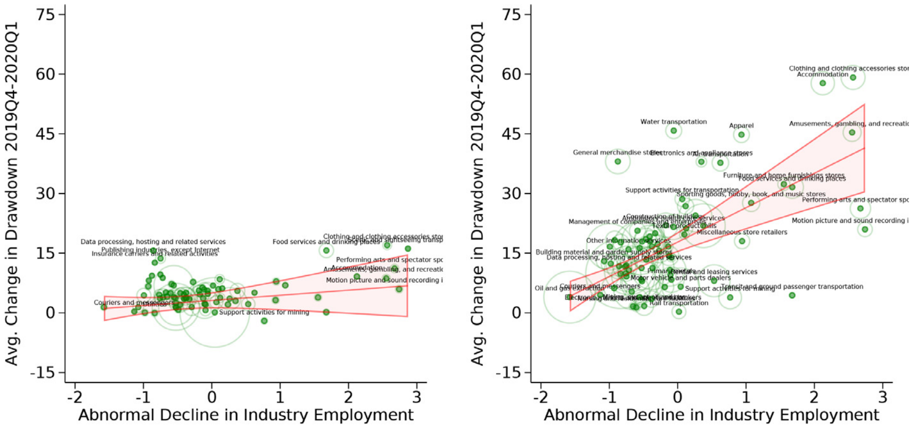
[25] Table A.10 reports the distribution of utilization rates in 2020Q1 and 2020Q2. Comparing to Table 7, the fraction of small SMEs with utilization below 10% fell by only 3 percentage points between 2019Q4 and 2020Q1. In contrast, the fraction of firms with more than \$5 billion in assets with utilization 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.

[26] 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
Revenue growth by industry exposure and size.

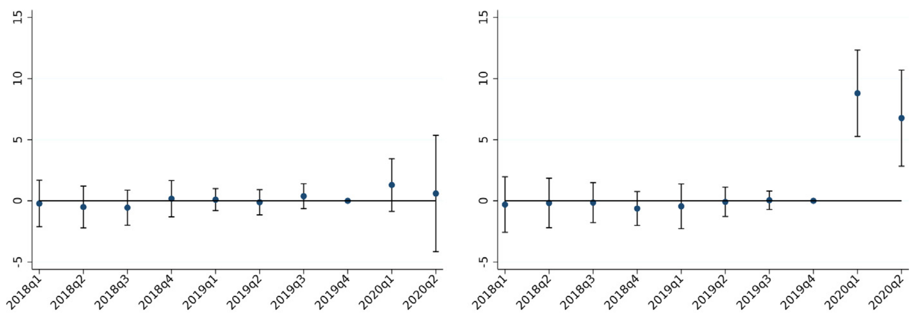
Dep. var.:	2020 Q1–Q3 YoY revenue growth in size-industry cell	
	Mean	Median
	(1)	(2)
0–250 (in mil.)	−6.81*	−9.10**
	(3.08)	(3.17)
1000+	−12.11**	−12.24**
	(2.92)	(3.00)
Exposure × 0–250	−13.22**	−14.14**
	(3.24)	(3.33)
Exposure × 1000+	−16.28**	−16.19**
	(3.19)	(3.28)
$P\{\beta_{\text{main},0\text{-}250} = \beta_{\text{main},1000+}\}$	0.21	0.47
$P\{\beta_{\text{interaction},0\text{-}250} = \beta_{\text{interaction},1000+}\}$	0.50	0.66
Observations	129	129

Notes: The table reports regressions of mean (column 1) or median (column 2) revenue growth through 2020Q3 relative to 2019Q1–2019Q3 within a size-industry cell. Size class is based on assets (in millions) in 2019Q4. Exposure is the three-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, standardized to have unit variance across industries.



(a) SMEs (Assets<\$250 million) (b) Large Firms (Assets>\$1 billion)

Fig. 3. Exposure to COVID-shock and credit line drawdowns for SMEs and large firms. Abnormal employment decline is the three-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 are restricted to industries with at least ten 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) <\$250 million (b) >\$1 billion

Fig. 4. Dyamics of credit line drawdowns for SMEs and large dirms during the COVID recession. The figure plots the sequence of coefficients $\{\beta_t\}$ obtained from estimating $\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \beta_t \times \text{Exposure}_i + \epsilon_{\ell,i,t}$, where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized to committed credit and Exposure_i is the three-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.

Table 13
Drawdowns by firm size and exposure to COVID-19 shock: abnormal three-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	0.6
	(2.3)	(2.2)	(1.4)	(1.3)	(1.3)	(2.0)
Exposure × 50–250 (in mil) × COVID		3.5***	2.4***	2.2***	2.1***	0.9*
		(1.3)	(0.8)	(0.8)	(0.7)	(0.5)
Exposure × 250–1000 × COVID		4.4**	3.3**	3.3**	3.4**	1.2
		(2.1)	(1.6)	(1.4)	(1.4)	(1.0)
Exposure × 1000–5000 × COVID		7.2***	6.1***	6.1***	6.1***	2.6***
		(2.2)	(1.7)	(1.5)	(1.4)	(1.0)
Exposure × 5000- × COVID		9.5***	8.2***	8.2***	7.8***	4.0**
		(3.2)	(2.8)	(2.7)	(2.6)	(1.8)
50–250 (in mil) × COVID		4.6***	3.3***	3.3***	3.0***	0.6**
		(0.5)	(0.6)	(0.6)	(0.5)	(0.2)
250–1000 × COVID		11.3***	9.5***	9.2***	9.2***	4.0***
		(1.2)	(1.0)	(0.9)	(0.9)	(0.6)
1000–5000 × COVID		15.4***	13.2***	12.9***	12.3***	5.6***
		(1.7)	(1.1)	(1.0)	(1.0)	(0.7)
5000– × COVID		18.0***	15.1***	14.7***	14.1***	5.5***
		(2.6)	(1.9)	(1.9)	(2.0)	(1.2)
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	60,117	60,117	60,117	60,117	54,264	39,561
N	756,529	756,529	756,529	756,527	685,096	497,754
R^2	0.83	0.83	0.83	0.83	0.83	0.86

Notes: Results from estimating a model of the following type: $\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \sum_{s\neq\{\$0-50m\}} \beta_{1,s}[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}] + \beta_2[\text{Exposure}_i \times \text{COVID}] + \sum_{s\neq\{\$0-50m\}} \beta_{3,s}[\text{Exposure} \times \mathbb{I}\{\text{size class} = s\} \times \text{COVID}] + \epsilon_{\ell,i,t}$. where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized to committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2, and Exposure_i is the three-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, operating income plus depreciation and amortization/assets, year-over-year sales growth, 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, and 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 three-digit NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

sets. Appendix Figure A.5 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 13, columns (3)–(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.5 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, and especially small firms, to access pre-committed credit.

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

Table 14
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	43,806	43,806	29,184	7195	3488	2403	1536
N	67,081	67,081	33,040	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 three-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 three-digit NAICS code.

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 14 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.[27] To ease interpretation, we report a cross-sectional specification with the dependent variable being 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.[28] The IV coefficient is smaller than the OLS coefficient but is estimated with less precision, and the data do not reject equality. The next several columns report the IV coefficient separately by firm size class. Consistent with the results in Table 13, 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 make 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 is central 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 do not explain 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% of respondents said it was due to a deterioration in their current/expected capital or liquidity

[27] 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/).

[28] 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 15
Aggregate drawdowns for PPP participants by firm size, 2019Q4–2020Q2.

	Non-PPP credit outstanding ($Bil)			PPP amount ($Bil)	Repayment ratio (%)	N
	2019Q4	2020Q1	2020Q2			
Firm assets ($mil)						
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	38,508
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	51,713

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.

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.6 in the Appendix corroborates the survey results by showing that loan-level default probabilities reported in the Y-14 rose in 2020. Critically, 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.[29]

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 which originated in capital and liquidity shortfalls on bank balance sheets,[30] 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.

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 two (later increased to five) years and a maximum interest rate of 4% (later set to 1%), to firms that have less than 500 employees or that satisfy certain other eligibility criteria. In addition, firms that maintained expenses over an eight-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.

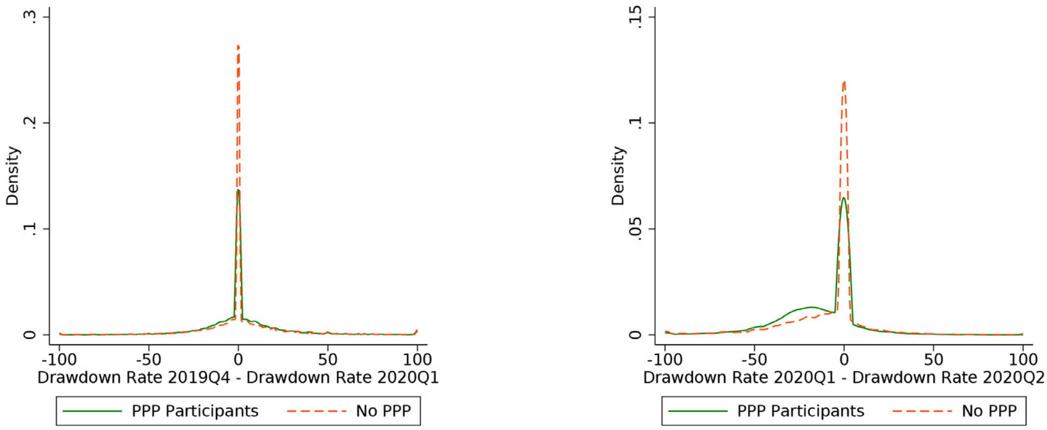
Table 15 reports the non-PPP loan balances for the firms we can identify as PPP recipients, as well as the PPP amount. We identify 51,713 current Y-14 borrowers as PPP recipients. Consistent with the eligibility rules for program participation, 97% of the PPP loans to Y-14 borrowers with nonmissing assets 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.[31] However, these firms account for a disproportionately large share of loan repayments in 2020Q2. Total credit outstanding to small SMEs fell by $28.9 billion in 2020Q2 (see

[29] If some lenders were constrained by regulatory capital, there might be a concern that the effect of drawdowns on regulatory capital are in part driving differential drawdowns across the firm size distribution. Under Basel I the incremental capital was larger for an origination maturity of less than one year, that is, in the short-term facilities predominantly used by small firms. However, Basel II significantly reduced the capital benefits of short term credit lines, particularly for lenders using the Foundational-IRB approach (more commonly applied by the larger banks in our sample) whose capital cost of undrawn credit is instead based on internal ratings (Plosser and Santos, 2018). Given that the internal risk rating maps directly to the increment in regulatory capital, this concern is inconsistent with differences in drawdowns across the firm size distribution remaining even after controlling for the internal risk rating and also with the differences holding across both larger and smaller banks.

[30] See, among others, Ivashina and Scharfstein (2010), Acharya and Mora (2015), Chodorow-Reich and Falato (Forthcoming), and Ippolito et al. (2019).

[31] 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

Fig. 5. Kernel density of drawdowns at small SMEs.

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.

Fig. 5 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. 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.[32]

[32] 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.

6. Conclusion

Smaller borrowers sign loan contracts with 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, or that large firms always can. Using the same regulatory dataset, Brown et al. (2021) find that small firms extensively draw on their credit lines to weather idiosyncratic cash-flow shocks in “normal” times. In fact, our theory predicts that granting control rights to lenders increases access to liquidity in normal times. On the other hand, 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 show 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, especially 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 can 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, these forces could 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, but also they 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.

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