Bank Liquidity Provision Across the Firm Size Distribution

Gabriel Chodorow-Reich, Olivier Darmouni, Stephan Luck, and Matthew Plosser*

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Abstract

Using loan-level data covering two-thirds of all corporate loans from U.S. banks, we document that SMEs (i) obtain much shorter maturity credit lines than large firms; (ii) have less active maturity management and therefore frequently have expiring credit; (iii) post more collateral on both credit lines and term loans; (iv) have higher utilization rates in normal times; and (v) pay higher spreads, even conditional on other firm characteristics. We present a theory of loan terms that rationalizes these facts as the equilibrium outcome of a trade-off between commitment and discretion. We test the model's prediction that small firms may be unable to access liquidity when large shocks arrive using data on drawdowns in the COVID recession. Consistent with the theory, the increase in bank credit in 2020Q1 and 2020Q2 came almost entirely from drawdowns by large firms on pre-committed lines of credit. Differences in demand for liquidity cannot fully explain the differences in drawdown rates by firm size, as we show that large firms also exhibited much higher sensitivity of drawdowns to industry-level measures of exposure to the COVID recession. Finally, we match the bank data to a list of participants in the Paycheck Protection Program (PPP) and show that SME recipients of PPP loans reduced their non-PPP bank borrowing in 2020Q2 by between 53 and 125 percent of the amount of their PPP funds, suggesting that government-sponsored liquidity can overcome private credit constraints.

*Chodorow-Reich: Harvard University, chodorowreich@fas.harvard.edu; Darmouni: Columbia University, omd2109@columbia.edu; Luck: Federal Reserve Bank of New York, stephan.luck@ny.frb.org; Plosser: Federal Reserve Bank of New York, matthew.plosserk@ny.frb.org. We thank seminar participants at Berkeley Haas for useful comments and Sungmin An, Harry Cooperman, and Alena Kang-Landsberg for excellent research assistance. The opinions expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System

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 their dry powder on paper may not materialize when needed. Yet, empirical evidence of differences between small and medium enterprises (SMEs) and large firms in their ability to arrange and access bank liquidity remains rare, as most analyses of loan terms and lending in the United States use data on syndicated loans that include only large borrowers and loans.

In this paper we investigate differences in the provision of bank liquidity across the firm size distribution. Using supervisory data covering two-thirds of all commercial and industrial loans, including 50,000 small and medium enterprises (SMEs), we present five facts about differences in loan terms to large and small firms that reflect lender *commitment* to the former and *discretion* to the latter. Relative to large firms, small firms obtain credit lines with much shorter maturity, have less active maturity management and as a result frequently have expiring credit, post more collateral, have higher utilization rates, and pay higher spreads even conditional on other firm characteristics. We then show that these differences in loan terms mattered to firms' ability to access liquidity during the COVID-19 recession. The increase in bank credit in 2020Q1 and 2020Q2 came almost entirely from drawdowns by large firms from pre-committed lines of credit, whereas small firms had no net drawdown of credit lines. Furthermore, large firms exhibited much higher sensitivity of drawdown rates to industry-level measures of exposure to the COVID recession, suggesting that differences in demand for liquidity cannot fully explain the differences in observed drawdown rates. Finally, we provide evidence that government-sponsored liquidity can overcome these frictions, as PPP recipients on net *reduced* their non-PPP bank borrowing in 2020Q2 despite not having drawn down in 2020Q1.

We start in section 2 with an illustrative framework of equilibrium loan term determination. The framework extends the Holmström and Tirole (1998) model of banks' liquidity provision to firms facing cash-flow and asset value shocks in the presence of limited asset pledgeability. Loan terms give lenders

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

either *commitment* or *discretion* in granting funds. With lender commitment, the borrower can always draw on credit limits determined ex-ante, while with discretion the lender can deny requests for funds ex-post. Both types of contracts can reduce credit constraints: commitment through an insurance channel by cross-subsidizing high shocks with low shocks, discretion by giving the lender an option to monitor and make funding contingent on ex-post asset values. In equilibrium, firms choose contracts that minimize the probability of liquidity-driven default. Discretion, implemented for example by a short-maturity credit line tied to collateral, is preferred for firms with pledgeable assets that are (i) smaller relative to cash-flow shocks, and (ii) more uncertain ex-ante, a description that resembles smaller firms. Intuitively, insurance is less valuable when large shocks are more likely, and discretion more valuable when the option value of monitoring is larger. Due to these equilibrium choices, small firms are more affected by the arrival of a large cash-flow shock. Having granted lenders significant discretion, small borrowers are less able to draw down their credit line despite having dry powder "on paper."

Section 3 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 bank with more than $100 billion in total consolidated assets. For each loan, the data contain information on loan terms (loan type, commitment, maturity, origination date, spread, collateral type, etc.) and borrower characteristics (industry, assets, sales, risk rating, etc.).

Section 4 presents five facts about bank loan terms across the firm size distribution in line with the model's prediction that lenders retain discretion in credit commitments to small firms. Fact 1 documents sharp differences in maturity at origination for credit lines, but not for other loan types. Among firms with fewer than $50 million in assets, three-quarters of credit lines have maturity of 1 year or less at origination and more than one-quarter of loans to these firms are demand loans immediately callable by the lender. The share of credit lines with less than 1 year maturity at origination declines to less than 10% for firms with more than $1 billion of assets, for which the median and modal credit line is a 5 year facility. These maturity differences disappear for term loans and capitalized lease obligations, for which the vast majority of credit to both small and large firms originates with 5 or more years of maturity.

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

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

Fact 4 shows that in normal times small firms have higher utilization rates on their credit lines than large firms. 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%. Small firms also exhibit larger sensitivities of utilization to the value of collateral.

Fact 5 covers loan pricing. Despite the shorter maturity on credit lines, less active liquidity management, and higher collateral requirements, small firms nonetheless pay higher spreads than large firms. We refer to this arrangement as small firms choosing loan terms from a different menu rather than choosing different items from the same menu as large firms. Differences in industry, lender, firm financials, and the lender's internal rating of the firm can explain only about one-third of the size gradient. Controlling additionally for other loan terms — maturity, collateral, and size — further reduces (but does not eliminate) the gradient, indicating that these other terms and spreads jointly reflect characteristics of the borrower not captured by financial variables or rating.

We then turn in section 5 to the provisioning of credit to small and large firms following the COVID-19 liquidity shock. Total outstanding C&I loans increased sharply in the first quarter of 2020. We first show that this overall increase almost entirely comprises of higher drawdowns of pre-existing credit lines by large firms, a point conjectured in Li et al. (2020) and documented in contemporaneous work by Greenwald et al. (2020). The higher drawdown rate at larger firms survives controls for lender and borrower industry, state, leverage, profitability, rating, 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, providing suggestive evidence that the more stringent terms to small firms prevented them from drawing down 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 liquidity shocks in the COVID recession. The controls for industry, state, and bond market access already help to alleviate this concern by removing the possibility of large firms operating in more severely impacted industries or states or having used their credit lines solely because of the bond market turmoil in March 2020. To further isolate credit constraints from demand factors, we next explore how the sensitivity of drawdowns to liquidity shocks varies across the size distribution.

We construct two measures of liquidity shocks. The first measure is the percent change in national employment in the firm's three digit industry between 2019Q2 and 2020Q2 less the trailing five year change. The abnormal change in employment provides an imperfect proxy for the demand shock to a firm, but the measure lines up fairly well with health-related risks and can be calculated for all firms. For example, the five industries with the largest declines in employment are scenic and sightseeing transportation, motion picture and sound recording studios, performing arts and spectator sports, clothing stores, and gambling. The second measure is the abnormal growth rate of national sales in the firm's three digit industry. This measure more closely accords with the theoretical notion of a liquidity shock but is available only for 13 industries included in the Census Retail Sales.

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

Finally, we provide evidence that government-provided liquidity can overcome the credit constraints that prevented SMEs from drawing on their credit lines. We match the Y-14 data to a list of participants in the Paycheck Protection Program (PPP) set up under the CARES Act. The PPP provided loans of up to $10 million to to firms with less than 500 employees or satisfying certain other eligibility criteria and further made these loans forgivable if the borrower kept qualifying expenses above specified thresholds. The SMEs in our data that received PPP funds *reduced* their non-PPP bank borrowing in 2020Q2 by between 53 and 125 percent of the amount of their PPP funds.

Related literature. The first contribution of our paper is to document how loan terms vary across the firm size distribution using a newly available supervisory data set with extensive coverage of both SMEs and large firms. In the United States, most of the evidence on loan terms comes from the syndicated loan market, which caters overwhelmingly to large borrowers and loans. Strahan (1999) provides an early and comprehensive analysis of how loan terms vary with size in the syndicated market. He finds that smaller firms in this market have loans with shorter maturity, post more collateral, and pay higher spreads. We show that these patterns become even more pronounced when extending to a sample that includes much smaller firms than appear in the syndicated market. In recent work, Lian and Ma (2020) argue for the primacy of cash-flow over asset-based lending for large firms. We confirm their results but show that for small firms, asset-based lending remains dominant. 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 some non-syndicated loans but few if any small SMEs. Petersen and Rajan (1994) and Berger and Udell (1995) study a survey of businesses with less than 500 employees with a focus on the effect of relationship strength on the quantity and price of credit. Agarwal et al. (2004) study a proprietary data set from a large financial institution of loan commitments made to 712 privately-held firms. The data sets in these papers mostly contain micro-enterprises that receive loans smaller than the $1 million cutoff for inclusion in the Y14 data. Technologies for lending to microenterprises and small SMEs differ, with the former typically using a score-based algorithm (Berger and Udell, 2006), making it more difficult to compare to large firms. In other countries, the existence of credit registries has made the analysis of loan terms to SMEs possible (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 the first evidence of credit constraints mattering in the COVID recession and to shed light on the role of PPP in alleviating them. In earlier work, Li et al. (2020) documented the sharp increase in bank credit outstanding in 2020Q1 and showed that this increase mostly came from large banks. Acharya and Steffen (2020) show that large firms drew down bank credit lines after the outbreak and raised cash levels. In independent and contemporaneous work, Greenwald et al. (2020) also find that the increase came entirely from credit line drawdowns by large firms. Li et al. (2020) conjectured that these drawdowns reflected large firms drawing on credit lines as a substitute for the bond market disruptions in March (Haddad et al., 2020). Our evidence of substantial drawdowns by firms without bonds outstanding and of the differential response to liquidity shocks by small and large firms instead emphasizes credit constraints facing small firms as a complementary channel for why only large firms drew liquidity.

More generally, our paper contributes to a debate on whether credit lines actually provide contingent credit when liquidity shocks arrive (Sufi, 2009; Santos and Viswanathan, 2020). Our empirical results show that smaller borrowers were especially vulnerable to being unable to tap their credit commitments following the breakout of COVID-19, in contrast to their use of credit lines in "normal times" (Brown et al., 2020). Due to data limitations, much of this debate has concerned large firms and the role of loan covenants (Roberts and Sufi, 2009; Chodorow-Reich and Falato, 2020; Ippolito et al., 2019; Murfin, 2012). We broaden this focus to include a more general trade-off between commitment and discretion that extends to other loan terms, including maturity and collateral. This is line with the practical relevance of incomplete contracting and control rights (Hart, 2001), which has lead to an extraordinary rich theory literature on loan terms.[2] Whereas these works consider many applications, we focus on the cross-sectional implications for liquidity provision trough credit lines. Other works have also studied aggregate liquidity constraints when the banking sector might not be able to honor all credit line draw-downs (Acharya et al., 2018; Greenwald et al., 2020).

The circumstances of the beginning of the COVID recession have additional implications for how to think about credit constraints in bad times across the firm size distribution (Gertler and Gilchrist, 1994). A common view emphasizes shocks to bank health and the cost of setting up new lending relationships as the primary source of credit constraints for small firms (Stiglitz and Weiss, 1981; Petersen and Rajan,

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

1994; Chodorow-Reich, 2014). We instead provide evidence that small firms did not draw on pre-existing credit lines at a time when the banking sector was flushed with funds. This evidence suggests the importance of the incomplete nature of financial contracting to understanding how bank liquidity flows across the firm size distribution.

2 Illustrative Framework

This section presents an illustrative framework that can explain differences in loan terms across firms of different size, as well as the implications of these differences for access to liquidity in bad times. We follow the extensive literature on bank lending that has drawn a distinction between committed and contingent access to credit, incorporating the role of control rights in incomplete contracting. Classical models show that committed credit lines can relieve financial constraints by providing *liquidity insurance* (Holmström and Tirole, 1998). However, there is empirical evidence 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.

The insurance and discretion view of bank liquidity are in direct conflict. Our focus is on how the trade-off between commitment and discretion vary across the size distribution. We provide a simple extension of the optimal contracting framework of Holmström and Tirole (1998) to answer two questions: (i) Is access to liquidity less likely to be committed for small firms? and (ii) Which firms are more affected by a large liquidity shock?

Setup The firm's problem is a simple version of Holmström and Tirole (1998) with one extension: the firms' assets have 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 $t = 0$, the firm signs a loan contract with a bank, consisting of a credit limit and loan terms that determine the extent of creditor control. At $t = 1$ a cash-flow shock realizes: per unit of assets, the firm needs to inject additional funds $\rho \sim \mathcal{N}(\mu, \sigma^2)$, where $\rho < 0$ has the interpretation of a surprise positive cash-flow shock. If the firm cannot meet this obligation, it fails and we assume for simplicity that nothing can be recovered. Finally, at $t = 2$ each unit of assets yields a payoff z. The key friction is limited pledgeability: the firm can promise (in expectation) only a share θ of its terminal value to lenders in order to obtain financing. The parameter θ captures the (inverse of) financial frictions and can be be micro-founded by moral hazard. The actual per-unit value of pledgeable assets is uncertain and equal to $\theta z + \epsilon$, where $\epsilon \sim G$ is mean zero and (for simplicity and inessentially) uncorrelated with ρ. The variance of ϵ captures "uncertainty" over the firm's asset values. The lender is risk-neutral and must break-even on the loan, assuming a discount rate of 0.

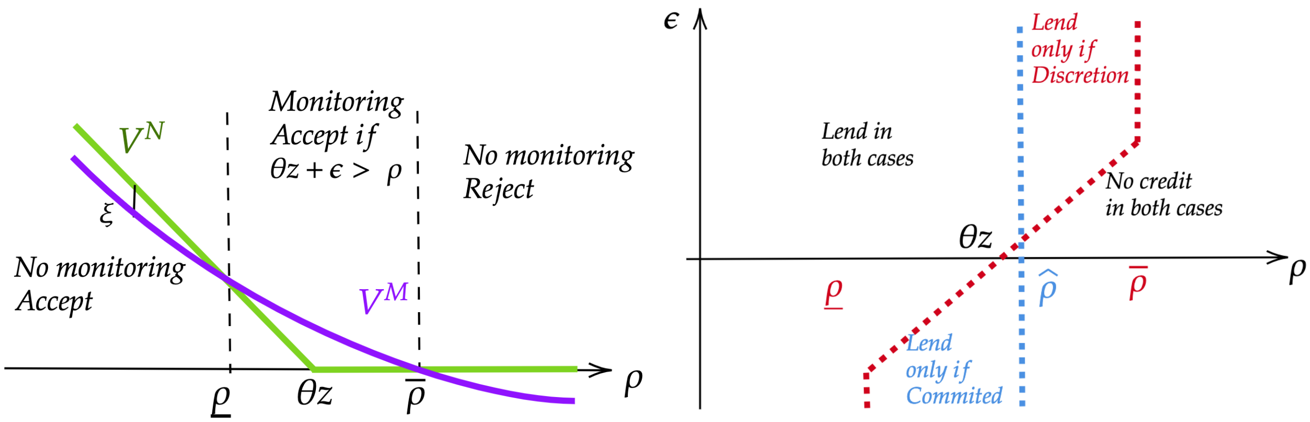
The firm's ability to continue its operations depends on the funds it can access at $t = 1$. A firm with credit limit $\hat{\rho}$ can sustain a shock as large as $\hat{\rho}$ and defaults for larger shocks. (We assume for simplicity no new investment opportunities arrive at $t = 0$ that could absorb financing). Because the cash-flow process is proportional to scale, firm size A plays no direct role. Instead, we will think of small firms as less profitable (lower z) and subject to greater financial frictions (lower θ), greater liquidity risk (higher μ), and more uncertain asset value (greater variance of ϵ).

Commitment vs. Discretion The firm chooses between two contractual forms: a committed credit line or a credit line with lender discretion. We model this choice as a dichotomy for simplicity; in practice the trade-off between commitment and discretion is implemented in a more continuous fashion. The model predictions should therefore not be interpreted as some firms always being able to draw, while others are never able to.

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

In the alternative contractual form, lender discretion introduces the possibility of monitoring before deciding to grant funds at $t = 1$. Monitoring is potentially valuable because of uncertainly over the true value of long-term assets. Events at date 1 unfold as follows: (i) the lender observes ρ, i.e. sales are down; (ii) the lender chooses whether to pay cost ξ per unit of assets in order to observe the shock ϵ to

[3]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 $\mathbb{E}[\rho|\rho < \hat{\rho}] = \mu - \sigma h\left(\frac{\hat{\rho} - \mu}{\sigma}\right)$.



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

Figure 1: *Model Properties*

long-term asset values; (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.

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 firms characteristic lead to discretion versus commitment? More details can be found in the Internet Appendix.

A first key property of the optimal discretion contract is that monitoring only occurs for intermediate values of the cash-flow shock ρ. Intuitively, small requests for funds are not alarming enough to justify incurring monitoring costs, while large requests are too alarming. Formally, let V^M and V^N denote the expected value to the lender of monitoring and not, respectively. Without monitoring, the lender agrees to lend only when ρ is less than pleageable assets 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 two cutoffs $\underline{\rho}, \overline{\rho}$ such that $V^M > V^N$ if $\rho \in [\underline{\rho}, \overline{\rho}]$. These cutoffs are defined implicitly by $\int_{\epsilon > \underline{\rho} - \theta z} \theta z + \epsilon - \underline{\rho} \quad dG(\epsilon) = \theta z - \underline{\rho} + \xi$ and $\int_{\epsilon > \overline{\rho} - \theta z} \theta z + \epsilon - \overline{\rho} \quad dG(\epsilon) = \xi$.[4] The left panel of fig. 1 illustrates the monitoring decision graphically.

The second key property is that the size of the monitoring range increases in uncertainty over the

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

firm's assets, captured by the variance of ϵ. Intuitively, when uncertainty is low, the *option value of learning* is low relative to monitoring costs. In fact, if uncertainty over firm's assets is too low, $V^M < V^N$ always and 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 $\hat{\rho} > \theta z$.

For firms with sufficiently large uncertainty over asset values, discretion can potentially dominate committed credit. Firms for which this is the case have pledgeable assets that are low relative to expected cash-flow shocks but also highly uncertain. The right panel of fig. 1 illustrates lending outcomes under both type of contracts. The figure makes clear the potential upside of discretion: it leads to more lending in the high shock region if fundamentals have improved. However, it gives up some lending in low shock regions. Therefore, only firms with sufficiently high expected cash-flow shocks and sufficiently high uncertainty prefer discretion. Intuitively, insurance is less valuable when large shocks are more likely, and discretion more valuable when the option value of monitoring is larger. The Internet Appendix shows that $\mathbb{E}[\rho] > \theta z$ is a second necessary condition for discretion to be preferred.

Connection to Loan Terms A contract with discretion can be implemented using terms such as demandable or short-maturity debt, collateral, or covenants. Demand loans perfectly concord with 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 possibly observe ρ before agreeing to renew the agreement and to make the renewal decision conditional on monitoring and the level of funds needed in the near future. With collateral, any time the borrower requests funds, the lender can monitor to verify the value of pledged assets and reject if the request is above this value. Covenants allow the lender to monitor and reject a drawdown request if the covenant is violated. Crucially, all of these terms involve discretion: a lender can roll-over the loan, not mark the collateral to market at high frequency, and waive a covenant violation.[5] Conversely, commitment is achieved through loan terms agreed upon at $t = 0$, for example by signing a long-term unsecured credit line with weak covenants.

Empirical Predictions This contracting framework delivers two predictions. First, it can rationalize differences in loan terms between small and large firms. Discretion is chosen by firms with pledgeable

[5]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, we find that strict loan terms tend be bundled together, suggesting broad economic forces that transcend any one loan term. Nevertheless, different loan terms give lenders discretion along different dimensions. For example, collateral requirements or covenants can be used to act on a piece of news at any time, but only if that information relates to a specific asset value or financial ratio. On the other hand, short maturity gives less frequent opportunities to exercise discretion but the renewal decision can be based on any type of information.

assets that are small relative to cash-flow shocks and more uncertain ex-ante. A vast literature associates these conditions with smaller firms that tend to be riskier, more opaque, and thus ulimately more constrained (Gertler and Gilchrist, 1994; Petersen and Rajan, 1994; Berger and Udell, 2006). We thus expect that small firms have short-term maturity credit lines that must be rolled-over continuously, pledge more collateral than large firms, and pledge collateral with uncertain final value such as accounts receivable, inventories, or blanket lien as opposed to fixed assets or real estate. The possibility of monitoring also requires arrangements ex ante as bankers and firm management must establish a relationship in order to set up a channel for information collection. Petersen and Rajan (1994); Berger and Udell (1995), and Degryse and Van Cayseele (2000) emphasize this relationship aspect of lending to small firms, as just sharing accounting information at $t = 1$ is unlikely to be credible enough given that these numbers are not easily verifiable nor forward-looking.[6]

Second, small firms with contracts that implement discretion may not be able to draw on their credit lines when a large cash-flow shock arrives, even if they have funds available "on paper". In contrast, large firms with harder commitments will draw. The resulting "evaporation" of liquidity to small firms is the result of an equilibrium choice: allowing credit limits to be information-sensitive raises the probability of accessing funds ex-ante, but hurts small firms when an especially large shock arrives.[7] Note however that this prediction is a matter of degree: we are not claiming that small firms can never draw nor that large firms are always able to.

3 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 test models. 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

[6] 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.

[7] It should be clear that monitoring and termination do not necessarily result from the large shock being unanticipated. In fact, firms sign contracts with discretion precisely because they expect large liquidity shocks. In principle, news that shifts the distribution of cash-flow shocks can also trigger renegotiation even before any liquidity need arises. Through the lens of the model, this can be thought as affecting the loan agreement at $t = 0$. News about future can be modeled either as (i) a right-shift of the distribution of cash-flow shocks; or (ii) an increase in uncertainty over firms' assets values. In both cases, our analysis shows that these forces make discretion relatively more attractive relative to committed credit lines. This implies that contracts that are newly signed or renegotiated after the shock are more likely to include stricter loan terms.

consolidated assets.[8]

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 sometimes abuse terminology somewhat and refer to these categories collectively as corporate loans. Banks report for each loan, in addition to its committed and utilized amount, a large set of characteristics, including the loan type (we distinguish between revolving and non-revolving credit lines, term loans, capitalized lease obligations), interest rate, spread, reference-rate, loan purpose, and remaining maturity. Further, loans are identified within a bank's portfolio across time with flags for new loan originations and renewals of existing facilities. Loan renewals refer to changes in the terms of the original loan agreement such as re-pricing or changes in the maturity. In contrast, if a facility has been renewed as part of a major modification, it obtains a new loan id and is flagged as a new origination.[9] 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, we find that around 5.7% of all facilities require the market value to be reported.

Banks also report data on the borrower, including location, industry, a bank-internal risk rating, total assets, debt, cash, accounts receivables, fixed assets, and inventory. These data can be obtained reliably for around 60% of all borrowers, with the data being more likely to be reported when firms are larger. Financial variables may not be updated in each quarter but instead updated annually or at loan origination/renewal.

We use borrowers' tax identification numbers to link their borrowers across banks and over time. We merge the Y-14 schedule with Compustat via the tax identifier, yielding 4,686 matched firms 2015Q1 and 2020Q2. Further, we use Compustat-Capital IQ and Mergent FISD to identify firms with access to the bond market. We identify 3,328 firms that either had a bond outstanding according to Compustat-Capital

[8]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.

[9]Loan renewals are only flagged explicitly starting 2014Q4.

IQ in 2017Q4 or issued a bond at some point from 2010 through 2020 according to Mergent FISD. Of those 3,328 firms, we are able to identify 2,135 in the Y14. Moreover, of the 367 firms that we identify as having issued a bond between March and July 2020 we are able to identify 337 in Y-14. We also merge our data with firms listed as participants in the Paycheck Protection Program (PPP). Out of the 639,335 firms that are listed as taking a PPP loan, 55,375 can be matched to the Y-14.

Coverage. To obtain a sense of the coverage, we benchmark the Y-14 data to the universe of corporate bank lending and to other commonly-used data sets. Our data cover roughly two-thirds of total corporate loan commitments from banks. Appendix table A.1 compares the dollar amount of loan commitments and outstanding in our data set to the universe of such loans reported on bank balance sheets as reported in the Y-9C data collection. 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. In 2019Q4, the Y-9C reported \$4.61 trillion of commitments and \$2.25 trillion of corporate loans outstanding. 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 commitments, of which \$3.42 trillion are C&I or real estate-backed. The Y-14 schedule at these banks contains \$3.15 trillion of corporate commitments, equal to 68% of total Y-9C lending.

Table 1 reports summary statistics of total commitment by firm size class. 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 and firms with fewer than \$50 million as small SMEs. The assets are as reported in Y-14 and correspond to the assets of the entity that is the primary source of repayment for the facility.

Panel A contains all loans outstanding in 2019Q4, aggregated up to the firm (i.e. borrowing entity) level. There are 40,000 small SMEs in the data, 9,400 firms with between \$50 and \$250 billion in assets, 3,600 firms with between \$250 billion and \$1 trillion in assets, 2,400 firms with between \$1 and \$5 billion, and 1,900 firms with more than \$5 billion in assets. The table reports total loan commitments to the firm, including the part of syndicated loans held by other lenders.[10] Among the small SMEs, the median loan commitment is just \$2.9 million, while among firms with more than \$5 billion in assets the median commitment is \$103 million. There are also a number of firms without assets reported that we will

[10]In particular, we use the reported participation interest to scale up syndicated credits and then de-duplicate any syndicated credits held by multiple Y-14 banks.

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

Firm Size	Committed Credit (in $mil)						
(Assets in Millions)	1^{st} Percentile	10^{th} Percentile	Mean	Median	90^{th} Percentile	99^{th} Percentile	Firms in Category
Panel A: All Firms							
Unclassified	1.0	1.1	32.6	2.5	25.0	650.2	46,081
0 – 50	1.0	1.0	5.6	2.9	13.9	35.0	40,239
50 – 250	1.0	2.0	29.4	15.0	70.0	197.4	9,373
250 – 1000	1.0	1.9	107.5	30.0	286.4	908.1	3,594
1000 – 5000	1.0	2.4	346.7	62.5	1,000.0	2,898.6	2,358
5000–	1.0	2.7	811.9	93.7	2,436.4	7,533.8	1,886
Panel B: Compustat							
0 – 50	1.0	1.0	5.8	2.9	13.5	34.0	971
50 – 250	1.0	1.7	34.2	18.5	89.3	205.0	497
250 – 1000	1.0	1.6	148.3	41.9	445.4	1,201.6	740
1000 – 5000	1.0	2.8	411.9	111.3	1,183.9	2,983.1	1,314
5000–	1.0	3.2	907.5	149.9	2,586.6	8,000.0	1,483
Panel C: Syndicated Bank Loans							
0 – 50	1.5	3.7	23.6	18.3	55.5	85.0	168
50 – 250	2.8	20.0	98.2	80.0	192.1	472.2	964
250 – 1000	6.8	48.4	270.6	192.6	537.8	1,297.9	1,135
1000 – 5000	7.9	101.9	712.7	490.3	1,583.5	3,380.2	1,094
5000–	39.3	203.6	1,877.3	1,179.9	4,501.8	10,650.9	768

Notes: The table reports the distribution of firm-level committed credit by firm size group. Firm-level commitments are imputed based on a bank's committed exposure and their reported participation interest. For syndicated credits, duplicates are eliminated prior to aggregation at the firm level. The sample includes all C&I loans in the Y-14 corporate loan schedule as of 2019Q4. It also includes distribution breakdowns by whether the firm appears in Compustat and whether the loan is syndicated.

exclude going forward. Most of these appear to be small firms based on the commitment amount, but a few may be quite large.

Panels B and C restrict to firms in Compustat and with syndicated loans, respectively, to compare to other commonly-used data sets. The distribution of firms in Compustat tilts to larger firms. Nonetheless, the Y-14 contain nearly 1000 Compustat firms with less than $50 million in assets and another 500 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. 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 contain only 168 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. For example, among small SMEs the median loan size is $2.9 million in the full sample and $18.3m in the syndicated sample, and among firms with between $50 and $250m in assets the median loan size is $15.0 million in the full sample and $80.0m in the syndicated sample. 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 small banks. Insofar as small banks use a different lending technology such as being more information intensive, restricting to a common set of lenders helps to sharpen the differences in lending to large and small firms. Indeed, we will sometimes include lender fixed effects in what follows.[11] In any case, table A.1 makes clear that our data include a macroeconomically relevant share of lending to SMEs. Second, the data exclude loan commitments of less than $1 million to micro-enterprises. 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. To assess this coverage restriction in dollar terms, we merge the Y-9C by holding company with the Reports of Condition and Income (Call Reports) and use Schedule RC-C Part II, which reports

[11] Higher information intensity and monitoring of small firms at small banks would likely exacerbate the tendency toward discretion we find for small firms at large banks. However, the idea that large institutions are disadvantaged in lending to opaque SMEs has been disputed (Berger and Udell, 2006). Chen et al. (2017) report a decline in small business lending at the four largest banks beginning around 2008, but this decline largely concentrated in the small business segment that falls below the Y-14 threshold and did not extend to the 21 other banks in our sample.

C&I and real estate-backed loans outstanding of less than $1 million. In both the Y-14 banks and the full Y-9C universe, loans of more than $1 million account for more than 90% of total C&I and real estate-backed lending.

4 Loan Terms Across the Firm Size Distribution

In this section we document five facts about loan terms across the firm size distribution that support discretion to small but not large firms, especially in the provision of credit lines.

Fact 1: Small firms have short-term credit lines, large firms have long-term credit lines. Other loan types have similar maturity across the size distribution. Table 2 reports the distribution of maturity at origination or renewal for all loans outstanding on December 31, 2019, by loan type and firm size.

Panel A restricts to revolving credit lines, the most common loan type and the one most closely tied to access to liquidity. 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 30% of all credit lines. An additional 23% of loans to these SMEs have duration of less than 1 year and another 24% have 364 day credit lines, so that more than three-quarters of credit lines to small SMEs have 1 year or less of maturity at origination. Less than 10% of credit lines to these firms originate with more than 2 years of maturity.

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

Panels B-D of table 2 show that these differences in maturity mostly or completely disappear for other loan types. For example, less than 20% of term loans to firms of any size class have original maturity of less than 2 years and the majority of term loans have original maturity of greater than 4 years. If anything, small firms have slightly longer maturity term loans at origination. This pattern makes sense through the lens of our theoretical framework, as lenders value discretion only when they have not yet released funds.

Table 2: ***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	.3	.23	.24	.16	.055	.024	.012	22350
50-250	.13	.12	.11	.16	.19	.27	.026	6369
250-1000	.064	.046	.04	.073	.19	.56	.037	4224
1000-5000	.026	.021	.016	.032	.14	.73	.036	5048
5000-	.019	.036	.058	.04	.12	.69	.043	5401
				Panel B: Non-revolving Credit Lines				
0-50	.018	.15	.076	.06	.082	.21	.39	2145
50-250	.015	.079	.04	.069	.14	.4	.26	1187
250-1000	.019	.049	.019	.072	.098	.52	.22	569
1000-5000	.0044	.048	.02	.042	.13	.63	.13	455
5000-	.0025	.15	.059	.076	.19	.42	.099	393
				Panel C: Term Loans				
0-50	.0014	.042	.025	.016	.077	.28	.56	9814
50-250	.00078	.038	.021	.022	.15	.43	.34	5158
250-1000	.0018	.025	.016	.037	.13	.47	.31	2737
1000-5000	0	.028	.015	.03	.16	.57	.19	2031
5000-	0	.071	.051	.085	.25	.39	.15	1765
				Panel D: Capitalized Lease Obligations				
0-50	0	.1	.039	.014	.082	.34	.42	439
50-250	0	.068	.031	.0047	.14	.27	.49	643
250-1000	0	.03	.0083	.0066	.16	.31	.49	603
1000-5000	0	.055	.011	.018	.21	.21	.5	707
5000-	0	.022	.014	.011	.26	.13	.56	1425

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

Fact 2: All firms actively manage maturity of long-term loans. Small firms do not actively manage maturity of short and medium term loans. Therefore, many small firms have expiring credit lines. Table 3 pools data over 2015-2020 to explore active liquidity 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 1 year or less of maturity at origination 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, and this pattern holds almost uniformly across the firm size distribution. For credit lines with original maturity between 1 and 4 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 differences disappear at the long end of the spectrum, where the median renewal on a credit facility with more than 4 years of maturity at origination occurs with three or more years of maturity remaining and if anything small firm renewals occur with more maturity left.

The patterns for term loans look similar, with the main difference that even small SMEs renew medium-term (1-4 years) term loans well in advance of expiration. However, as shown in fact 2, most term loans to both small and large firms have more than 4 years of maturity at origination. Across the size distribution, the median renew on these loans occurs with around 4 years of maturity remaining.

Since the largest firms have primarily long-term credit lines and term loans (fact 1), the evidence in Table 3 confirms the active liquidity 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 4 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 1 year and the modal loan had maturity remaining of around 3 years, consistent with evidence from the syndicated loan market documented in Chodorow-Reich and Falato (2020). In sharp contrast, nearly 40% of loans to the smallest SMEs were immediately callable or due in the first quarter of 2020 and 85% were due sometime in 2020. Appendix table A.2 repeats table 4

Table 3: ***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	227899	1	19	62389	7	31	25757	55	60	15146
50-250	0	12	39471	6	21	24000	12	34	31371	38	60	36226
250-1000	0	12	9590	9	21	8255	21	35	27919	35	60	52369
1000-5000	0	12	5462	12	20	5570	26	36	34606	38	60	84312
5000-	1	12	12245	12	20	5630	29	37	28241	44	60	86646
Panel B: Term Loans												
0-50	0	4	13064	3	18	5215	20	34	24970	44	63	115065
50-250	0	6	6239	7	17	4574	23	34	24976	43	60	76870
250-1000	0	10	2028	12	18	2171	25	34	12910	43	58	39711
1000-5000	1	11	1743	13	20	1609	27	34	12087	44	58	31453
5000-	1	7	4273	12	19	3097	29	34	11940	46	57	21548

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.

separately for Compustat and non-Compustat firms and shows that the size differences hold within each of these sub-samples.

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

Fact 3: Small firms almost always post collateral while large firms often borrow unsecured. Table 5 reports the distribution of loans by firm size and the main type of collateral posted, if any, as of the end of 2019. The Y14 groups collateral types into real estate, fixed assets, accounts receivable & inventory (AR&I for short), cash, other specified assets, blanket lien, and unsecured. These collateral types differ in the protection they provide to a lender and the frequency of revaluation. Real estate and fixed assets are illiquid claims with stable valuations. AR&I are more liquid claims whose value can move at arbitrarily high frequency depending on the reporting requirements imposed by the lender, causing the effective loan limit to fluctuate as well. Blanket liens give a lender priority over unsecured lenders in bankruptcy but do not otherwise provide a specific claim.

As shown in Panel A1 and in line with facts documented in Luck and Santos (2020), less than 10% of non-demand revolving credit lines to SMEs are unsecured. Within those that are collateralized, half are backed by AR&I, with blanket liens accounting for most of the remainder. The share unsecured rises to 17% for revolving credit lines to firms with assets between $250 million and $1 billion, 30% for loans to firms with assets between $1 and $5 billion, and 70% 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 85% of demand loans to the largest firms unsecured, and AR&I again provide the dominant source of collateral.

Differences in collateral requirements are equally stark for term loans, shown in Panel C. Only 2% of term loans to firms with less than $50 million of assets are unsecured. Different from credit lines, the modal security for these loans is real estate. The share unsecured remains below 6% for loans to firms with assets between $50 million and $1 billion, but for these firms fixed assets become a more prominent source of collateral and real estate less so, perhaps reflecting the difficulty of verifying the value of fixed assets of small firms. The share unsecured rises to 23% for loans to firms with assets between $1 and $5 billion and 45% for the largest firms.

Table A.3 in the Appendix repeats table 5 separately for Compustat and non-Compustat firms and shows that the size differences remain within each of these sub-samples. Appendix table A.5 documents

Table 4: ***Remaining Maturity by Facility Type and Firm Size Category for Loans Outstanding on December 31, 2019***

Loan Due:	Demand	Jan	Feb	Mar	Q2	Q3-Q4	2021	2022-24	Later	Obs.
Assets ($mil.)										
Panel A: Revolving Credit Lines										
0-50	.28	.028	.029	.031	.2	.27	.099	.049	.0082	31169
50-250	.18	.017	.016	.019	.084	.16	.19	.32	.014	8804
250-1000	.13	.004	.005	.0034	.043	.077	.15	.58	.012	5954
1000-5000	.1	.0015	.0023	.0019	.015	.036	.11	.72	.0072	7380
5000-	.078	.0075	.0059	.0065	.022	.05	.086	.73	.014	7500
Panel B: Non-revolving Credit Lines										
0-50	.018	.019	.012	.017	.056	.088	.08	.36	.33	3002
50-250	.019	.01	.0075	.011	.046	.074	.13	.56	.13	1601
250-1000	.023	.0039	.0052	.0052	.03	.054	.11	.63	.13	773
1000-5000	.0063	.011	.0079	.0094	.027	.03	.079	.76	.066	636
5000-	.0015	.083	.06	.031	.046	.085	.12	.53	.04	648
Panel C: Term Loans										
0-50	.0015	.0042	.0064	.0069	.019	.037	.065	.38	.48	16027
50-250	.0011	.0052	.0053	.0076	.02	.041	.12	.55	.25	7354
250-1000	.0022	.0028	.0028	.0036	.019	.043	.12	.62	.19	3619
1000-5000	0	.0024	.0028	.0094	.018	.031	.091	.72	.13	2543
5000-	0	.013	.01	.0094	.043	.084	.14	.59	.1	2225
Panel D: Capitalized Lease Obligations										
0-50	0	.014	.0035	.01	.031	.059	.057	.54	.27	577
50-250	0	.0093	.0035	.0012	.0082	.042	.084	.57	.27	857
250-1000	0	.0037	.0025	.0075	.014	.052	.1	.59	.23	802
1000-5000	0	.0051	.001	.0031	.016	.045	.1	.53	.3	976
5000-	0	.0077	.0029	.0077	.019	.042	.14	.47	.3	2075

Notes: The table reports the fraction of loans to each firm size group (assets in $milion) with remaining maturity indicated in the table header. The sample includes all C&I loans in the Y-14 corporate loan schedule outstanding as of December 31, 2019.

Table 5: ***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	.019	.012	.49	.031	.045	.37	.032	22464
50-250	.025	.023	.45	.058	.077	.29	.084	7209
250-1000	.013	.041	.37	.055	.093	.25	.17	5202
1000-5000	.0045	.043	.32	.039	.11	.19	.3	6626
5000-	.0016	.017	.11	.014	.073	.082	.7	6916
Panel A2: Revolving Credit Lines (Demand Loans)								
0-50	.0075	.0072	.69	.021	.039	.17	.071	9183
50-250	.0063	.014	.39	.039	.036	.13	.38	2235
250-1000	.0023	.017	.2	.032	.019	.067	.66	1316
1000-5000	.00088	.0096	.11	.0035	.011	.053	.81	1142
5000-	0	.0061	.077	.0012	.022	.037	.85	819
Panel B: Non-revolving Credit Lines								
0-50	.34	.0085	.17	.096	.043	.33	.019	2949
50-250	.18	.012	.27	.08	.072	.36	.027	1571
250-1000	.15	.03	.27	.045	.081	.37	.066	755
1000-5000	.03	.057	.27	.052	.047	.29	.26	632
5000-	.034	.025	.11	.036	.043	.14	.61	647
Panel C: Term Loans								
0-50	.44	.0052	.13	.14	.027	.24	.021	16003
50-250	.24	.011	.14	.33	.042	.22	.022	7346
250-1000	.13	.02	.13	.39	.05	.22	.056	3611
1000-5000	.066	.031	.15	.19	.08	.25	.23	2543
5000-	.018	.018	.092	.2	.073	.16	.45	2225
Panel D: Capitalized Lease Obligations								
0-50	0	0	.19	.74	.028	.01	.026	577
50-250	0	0	.16	.79	.029	0	.02	857
250-1000	0	.0012	.072	.89	.011	.0012	.02	802
1000-5000	.0031	.002	.09	.87	.027	.001	.0051	976
5000-	.0058	.0024	.076	.85	.038	.0058	.028	2075

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

Table 6: ***Drawdown of Revolving Credit Lines by Firm Size, 2019Q4***

	Utilization/Commitment						
Assets (mil.)	< 10%	10–30%	30–50%	50–70%	70–90%	> 90%	Obs.
0-50	.33	.086	.12	.15	.14	.17	31160
50-250	.36	.11	.13	.15	.14	.13	8792
250-1000	.37	.12	.15	.15	.11	.094	5936
1000-5000	.47	.15	.13	.11	.074	.064	7363
5000-	.76	.088	.055	.032	.017	.05	7458

Notes: The table reports the mean fraction drawn credit as share of total commitments values.

differences in collateral posting across industries; for example, firms in the retail sector have a higher propensity to post AR&I, reflecting their need for working capital and their large inventories. However, these differences do not explain the size gradient in collateral, as we confirm in regressions that control for industry reported in table A.6 in the Appendix.

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

Fact 4: In normal times, small firms utilize credit lines at a higher rate and exhibit higher sensitivity of utilization to collateral value. Table 6 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 7% of the largest firms. Conversely, three-quarters of the largest firms had utilization rates below 10%, compared to one-third of small SMEs.

Figure A.4 reports the elasticity of utilization to collateral values. The top left panel shows how the elasticity varies across the firm size distribution. The figure reports the size-class coefficients $\{\beta_s\}$ from estimating the regression over 2015-2020:

$$\Delta \ln \text{Utilization}_{\ell,t} = \sum_s \beta_s \left[\mathbb{I}\{\text{size class} = s\} \times \Delta \ln \text{Collateral value}_{\ell,t}\right] + \Gamma' X_{\ell,t} + \epsilon_{\ell,t}, \tag{1}$$

where Utilization$_{\ell,t}$ is the utilized value for loan ℓ in quarter t, Collateral value$_{\ell,t}$ is the market value of collateral, and $X_{\ell,t}$ contains the change in log of commitment values interacted with size bins, categorical variables for collateral type, size bin, six bins of utilization relative to commitment and of utilization relative to collateral, and bank$\times$time, industry$\times$time, and rating$\times$time fixed effects. SMEs have economically and statistically much larger sensitivities of drawdown to collateral value, with an average elasticity around 0.65 for SMEs and below 0.3 for the largest firms.

The top right panel, (b), reports the elasticity separately by collateral type and firm size. Across collateral types, the sensitivity of utilization to collateral values generally increases from cash and other collateral to accounts receivable and real estate backed facilities.

The bottom left panel, (c), reports the elasticity separately by utilization rate. As utilization relative to collateral increases, the sensitivity of utilization to the value of collateral also increases. The average coefficient ranges from a low of 0.2 to a high for loans greater than 90% utilized of roughly 0.7. When we restrict to accounts receivable facilities in the lower right, panel (d), the relation is even clearer with the <10% utilized facilities exhibiting an elasticity of 0.25 and the greater than 90% used facilities showing an elasticity above 0.9.

Fact 5: Small firms pay higher spreads, even conditional on observable firm and bank characteristics. Facts 1-4 document that smaller firms have shorter maturity credit lines, as a result have less active liquidity management, and post more collateral than larger firms. Our final fact shows that small firms do not receive the benefit of lower spreads in exchange for these stricter loan terms. We refer to this arrangement as small firms choosing loan terms from a different menu rather than choosing different items from the same menu as large firms.

Table 7 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 who face the lowest spreads. Appendix table A.4 confirms that the size gradient holds within both Compustat and non-Compustat sub-samples.

Table 8 shows that observable characteristics of the borrower and lender cannot fully explain these differences. Columns (1) and (7) report regressions of the interest rate on size class and reference-rate$\times$time fixed effects, with loans to the smallest SMEs the omitted category. Thus, the coefficients have the interpretation of the additional spread, in basis points, for firms in each size class relative to the smallest SMEs. For both credit lines (column 1) and term loans (column 7), the unconditional differences in spreads are economically large;[12] the mean spread on a loan to a firm with more than $5 billion in assets is more than 100 basis points lower than to a small SME. Columns (2) and (8) show that adding industry$\times$time fixed effects does not reduce the size gradient in spreads. Adding lender fixed effects

[12] A similar relationship is present for non-revolving credit lines and capitalized lease obligations, see Table A.7 in the Appendix.

Table 7: ***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	.014	.0051	.059	.3	.41	.17	.039	20365
50-250	.054	.013	.14	.43	.21	.067	.082	5901
250-1000	.068	.014	.16	.36	.21	.082	.11	4026
1000-5000	.1	.015	.2	.38	.16	.074	.073	4644
5000-	.21	.022	.23	.35	.1	.046	.043	2344
				Panel B: Non-revolving Credit Lines				
0-50	.12	0	.016	.37	.35	.1	.037	3002
50-250	.11	.0025	.057	.41	.27	.095	.064	1601
250-1000	.12	0	.074	.42	.26	.079	.052	773
1000-5000	.038	.0063	.16	.57	.16	.041	.02	636
5000-	.099	.034	.34	.45	.065	.0077	.0046	647
				Panel C: Term Loans				
0-50	.019	.0017	.028	.38	.42	.13	.026	16027
50-250	.027	.0022	.071	.49	.29	.075	.046	7352
250-1000	.027	.0028	.12	.45	.26	.07	.066	3619
1000-5000	.033	.012	.19	.54	.15	.041	.031	2543
5000-	.091	.018	.26	.49	.11	.023	.011	2225
				Panel D: Capitalized Lease Obligations				
0-50	.053	.0071	.073	.3	.36	.16	.053	565
50-250	.032	.024	.23	.35	.24	.079	.042	851
250-1000	.01	.041	.28	.37	.2	.072	.026	796
1000-5000	.01	.031	.29	.36	.22	.047	.037	957
5000-	.018	.04	.33	.36	.13	.039	.082	2011

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 for revolving credit and non-revolving credit lines are only reported if the drawdown is strictly larger than zero. The sample includes all loans in the Y-14 corporate loan schedule as of December 31, 2019.

in columns (3) and (9) to absorb any differences in banks serving large and small firms substantially increases the explanatory power of the regressions, but only slightly reduces the gradient for credit lines and has no impact on the gradient for term loans. Columns (4) and (10) additionally include firm rating and financial characteristics — debt/assets, operating income/assets, and net income/assets— each interacted with a time fixed effect. The firm rating is assigned by the lender and maps into a probability of default. Including all of these variables 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 remains with for example an 80 basis point spread between loans to the smallest SMEs and largest firms conditional on industry, lender, rating, and leverage. This difference reflects aspects of small borrowers that make them risky beyond observable characteristics, such as concerns about mis-reporting of financial statements and soft information collected by the lender.

Columns (5) and (11) additionally control for maturity bin and collateral type×time fixed effects. Controlling for these other loan terms dramatically reduces the size gradient for credit lines. Interpreting this evidence requires care, because loan terms and interest rates are jointly determined. Nonetheless, 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 some other information about credit worthiness or market power not encoded in the rating. Put differently, the reduction in the spreads gradient signifies an omitted variable such as borrower quality that is positively correlated with size and maturity and negatively correlated with collateral and spreads, as suggested by our theory. Finally, column 6 shows that differences in utilization of credit lines across small and large firms (fact 4) do not add any explanatory power to spreads on top of the fixed effects and other loan terms.[13]

5 COVID and Drawdowns

We now assess how differences in loan terms impacted firms' access to liquidity in the first half of 2020. We first discuss raw differences, then credit line drawdown rates controlling for firm characteristics, then present evidence of heterogeneous drawdown rates in response to liquidity shocks, and finally discuss the role of PPP.

[13]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 8: ***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)	(8)	(9)	(10)	(11)
50-250 (in mil)	-56.5***	-58.2***	-39.5***	-34.9***	-10.5***	-10.5***	-16.5***	-15.4***	-15.0***	-12.5***	-11.8***
	(1.9)	(1.9)	(1.7)	(1.6)	(1.8)	(1.8)	(2.5)	(2.4)	(2.1)	(1.9)	(1.8)
250-1000	-49.2***	-59.1***	-44.1***	-36.2***	-1.5	-1.2	-15.7***	-18.2***	-17.9***	-11.4***	-7.8*
	(3.5)	(3.5)	(3.2)	(2.7)	(3.3)	(3.3)	(4.3)	(4.0)	(3.6)	(3.2)	(3.3)
1000-5000	-76.0***	-86.8***	-73.6***	-58.9***	-12.9***	-12.1***	-68.4***	-76.8***	-73.7***	-52.8***	-40.4***
	(3.3)	(3.2)	(3.3)	(2.8)	(3.6)	(3.6)	(3.8)	(3.5)	(3.6)	(3.1)	(3.4)
5000-	-113.3***	-124.8***	-107.9***	-80.4***	-24.0***	-23.5***	-109.2***	-116.0***	-115.5***	-79.6***	-63.2***
	(4.0)	(4.1)	(4.4)	(4.2)	(5.4)	(5.5)	(4.0)	(4.0)	(3.8)	(3.4)	(4.1)
Reference-Rate-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Rating-Time FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes
Firm Financial Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes
Loan Terms Controls	No	No	No	No	Yes	Yes	No	No	No	No	Yes
Drawdown	No	No	No	No	No	Yes	Yes	No	No	No	Yes
No of Firms	37418	37395	37394	35899	35717	35717	27185	27170	27168	26293	26211
N	119190	119139	119125	111912	109323	109323	54833	54796	54786	53460	52105
R^2	0.401	0.422	0.511	0.558	0.563	0.563	0.287	0.326	0.424	0.507	0.508

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

$$\begin{aligned}\text{Interest}_{\ell,t} = {} & \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \mathbb{I}\{\text{size class} = s\} + \beta_2 \frac{\text{Debt}}{\text{Assets}}_{i,t-1} + \beta_3 \frac{\text{Operating Income}}{\text{Interest Expense}}_{i,t-1} + \beta_4 \frac{\text{Net Income}}{\text{Assets}}_{i,t-1} \\ & + \sum_{m \neq \{0-6\text{ months}\}} \beta_{5,m} \mathbb{I}\{\text{maturity class} = m\} + \sum_{j \neq \{\text{Unsecured/BL}\}} \beta_{6,j} \mathbb{I}\{\text{collateral class} = j\} + \beta_7 \text{LoanSize}_{\ell,t} + \beta_7 \text{Drawdown}_{\ell,t} \\ & + \text{Reference-Rate-Time FE} + \text{Industry-Time FE} + \text{Bank-Time FE} + \text{Rating-Time FE} + \epsilon_{\ell,t}\end{aligned}$$

where $\text{Interest}_{\ell,i,b,t}$ is the interest on facility ℓ from bank b to firm i at time t. We group the firms in 5 size class categories (by asset size in $million), and consider 6 maturity class categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years) and 6 types of collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien). $\text{LoanSize}_{\ell,t}$ is the log of the committed loan limit. We restrict the sample to originations and renewals between 2015Q1 and 2019Q4.
Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 9: *Aggregate Drawdowns in $B by Firm Type, 2019Q4-2020Q2*

	Total Credit			Term Loans			CL Drawdowns (all facilities)			CL Drawdowns (pre-existing facilities)		
	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2
Panel A: By Firm Size (in Assets in $mil)												
Not classified	273.6	289.6	273.4	104.4	107.5	107.6	114.0	128.9	109.9	104.3	121.1	98.7
0-50	137.9	139.9	118.0	47.3	47.8	47.9	79.3	80.4	55.8	77.3	78.5	53.7
50-250	163.3	167.1	143.6	52.4	52.3	50.2	92.6	96.5	74.3	91.1	94.9	72.3
250-1000	160.5	179.3	157.9	50.6	51.3	47.5	91.2	109.5	90.6	89.7	107.9	88.5
1000-5000	218.6	277.6	236.2	65.8	68.4	64.5	122.9	179.7	141.2	121.9	178.7	139.4
5000-	316.6	485.6	388.4	127.9	150.8	143.8	106.3	250.0	158.7	105.2	248.1	155.3
Sum	1270.5	1539.0	1317.5	448.3	478.1	461.6	606.4	845.0	630.5	589.6	829.2	607.8
Panel B: Other Firm Characteristics												
Bond Market Access	348.1	525.6	421.9	130.7	152.2	144.7	134.8	288.8	190.8	132.8	286.8	186.9
Bond Issued March-July	100.1	174.7	128.2	38.7	47.0	41.1	29.8	95.5	56.1	29.4	95.1	55.5
PPP, 0-50	80.1	80.8	61.8	16.7	16.7	16.8	58.7	59.3	39.9	57.7	58.3	38.8
PPP, 50-250	64.3	65.2	53.9	15.0	15.0	14.5	43.7	44.4	33.2	43.4	43.9	32.8

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

5.1 Drawdowns by Firm Size

Table 9 displays the change in credit by firm 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 PPP credit. 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 43% in 2020Q1. These differences overwhelmingly reflect drawdown rates on existing credit line facilities, as shown in the right-most panel of the table. 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 shows that the large drawdown at large firms does not solely stem from bond market disruptions in March 2020, as large drawdowns occurred even at firms that have never accessed the bond market. On the other hand, the contraction in drawn credit at SMEs in 2020Q2 appears concentrated in firms that received PPP loans, a result we return to in section 5.3.

Table 10 reports 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 9 showed that almost all of the increase in bank credit outstanding occurred on these lines. The specification in column (1) takes the form:

$$\text{Drawdown}_{\ell,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_s \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \epsilon_{\ell,t}, \tag{2}$$

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit and COVID is an indicator for 2020Q1 or 2020Q2. Thus, column (1) includes only time and loan fixed effects and the coefficients on the interaction terms have the interpretation of the additional drawdown in 2020 for firms in the indicated size class relative to small SMEs. Drawdown rates rise monotonically in firm size, with the largest size class exhibiting a 14 percentage point larger increase in drawdowns in 2020. In all regression analysis in this section we cluster standard errors by three digit NAICS industry. 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.

The next columns add various controls to try to isolate the channels through which firm size matters to drawdowns. Column (2) adds an indicator for whether the firm has issued bonds, interacted with

Table 10: ***Drawdowns by Firm Size.***

Dependent variable	Drawdown Rate (in ppt)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)
50-250 (in mil) × COVID	3.8***	3.8***	2.7***	2.7***	1.7***	1.8***	0.4	0.6**
	(0.9)	(0.9)	(0.6)	(0.6)	(0.6)	(0.6)	(0.4)	(0.3)
250-1000 × COVID	9.4***	9.2***	8.0***	7.9***	5.8***	6.0***	3.2***	3.4***
	(1.6)	(1.6)	(1.1)	(1.1)	(1.0)	(1.0)	(0.9)	(0.8)
1000-5000 × COVID	13.6***	13.0***	11.4***	11.2***	9.1***	9.4***	5.9***	6.6***
	(1.8)	(1.9)	(1.2)	(1.2)	(1.1)	(1.1)	(1.0)	(0.9)
5000- × COVID	14.4***	13.4***	11.2***	10.9***	8.6***	9.3***	5.5***	5.6***
	(2.3)	(2.1)	(1.6)	(1.6)	(1.5)	(1.5)	(1.6)	(1.4)
Bond Market × COVID		1.2	1.2	1.2	1.1	1.4	1.1	0.6
		(1.0)	(1.0)	(0.9)	(0.9)	(0.8)	(0.8)	(0.8)
Demand Loans × COVID							-4.2***	-2.3**
							(0.5)	(0.9)
6-12 month × COVID							0.8*	0.5
							(0.4)	(0.3)
1-2 years × COVID							1.9**	1.5*
							(0.9)	(0.8)
2-4 years × COVID							5.5***	3.5***
							(1.3)	(1.0)
More than 4 years × COVID							7.1***	5.1***
							(1.3)	(0.9)
Real Estate × COVID							-0.1	0.8
							(1.6)	(1.3)
Cash × COVID							0.0	-0.2
							(0.7)	(0.7)
AR+Inventory × COVID							-1.8***	-1.2***
							(0.4)	(0.3)
Fixed Assets × COVID							-0.8	-0.2
							(0.7)	(0.6)
Other × COVID							0.2	0.4
							(0.7)	(0.7)
Spread × COVID								216.2**
								(83.9)
Drawdown 2019Q4× COVID								
20-40 Drawdown 2019Q4 × COVID								-1.9
								(2.7)
40-60 Drawdown 2019Q4 × COVID								1.0
								(3.9)
60-80 Drawdown 2019Q4 × COVID								-15.9***
								(6.0)
80-100 Drawdown 2019Q4 × COVID								-7.0***
								(0.9)
Loan FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No	No	No	No
Bank-Time FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	No	No	No	Yes	Yes	Yes	Yes
Financials	No	No	No	No	No	Yes	Yes	Yes
Rating-Time FE	No	No	No	No	No	Yes	Yes	Yes
No of Firms	51330	51330	51330	51330	51327	49763	49763	36979
N	581381	581381	581381	581381	581339	561015	560961	419372
R^2	.83	.83	.83	.83	.84	.84	.84	.84

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

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

$$\sum_{m \neq \{0-6 \text{ months}\}} \beta_{3,m} \left[\mathbb{I}\{\text{maturity class} = m\}\right] \times \text{COVID} + \sum_{j \neq \{\text{Unsecured/BL}\}} \beta_{4,j} \; \mathbb{I}\{\text{collateral class} = j\}\right] \times \text{COVID} + \epsilon_{\ell,t}$$

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit and COVID is an indicator for 2020Q1 and 2020Q2. We restrict the sample to outstanding loans from 2017Q4 onwards. Bond Market_i indicates whether firm i has issued bonds at any point between 2010 and 2020Q2. In column (7), we also control for maturity class and collateral type of loan ℓ, omitting the 0-6 month and unsecured loans and blanket liens. Robust standard errors are clustered at the three digits NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

COVID, to capture differences in loan demand arising from the bond market disruptions in March 2020. The coefficient on this term indicates a small (1 p.p.) additional drawdown among firms in the bond market over and above the size gradient. Including it only barely dents the size gradient, indicating that disruptions in the bond market by themselves cannot explain the large size gradient in drawdowns. Column (3) replaces the time fixed effect 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. Adding all of these fixed effects collectively reduces the size gradient somewhat but leaves a still sharp and highly statistically significant difference in drawdown rates between small SMEs and larger firms. Column (6) adds controls for two measures of leverage commonly used in covenants, debt/assets and operating income/interest expense, a measure of profitability, net income/assets, and categorical variables for the internal firm rating, each interacted with COVID. These controls slightly *increase* the size gradient, echoing our finding in fact 5 above that observable firm characteristics cannot explain the pricing gradient by firm size.

Column (7) includes controls for collateral type and maturity bin, interacted with COVID. The coefficients on these covariates indicate that demand loans have lower drawdown rates and long-maturity loans higher drawdown rates than do short-term credit lines, and loans backed by accounts receivable and inventory (AR&I) have lower drawdown rates than credit lines backed by blanket liens or unsecured. These coefficients make sense in our theory. Demand loans provide lenders complete discretion to terminate credit commitments while short-maturity credit lines offer more discretion than long-maturity since lenders can threaten not to rollover the credit line when it becomes due. Lenders can also re-value AR&I collateral at a high frequency and have some discretion in how to adjust the book value of these assets. Including these controls also reduces the size gradient by about 40%, reflecting the shorter maturity (facts 1 and 2) and higher collateral requirements, especially in AR&I (fact 3), of credit lines to small firms. We therefore interpret column (7) as evidence consistent with restrictive loan terms inhibiting access to liquidity in the COVID recession, and these restrictions binding most tightly on small firms. However, these terms do not completely eliminate the gradient and we do not have valid instruments for the loan terms that would allow us to claim causality of this evidence.

Finally, column (8) additionally controls for the spread and the 2019Q4 utilization rate bin, each interacted with COVID.[14] The spread control helps to absorb differences in drawdowns resulting from

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

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.[15]

5.2 Drawdowns by Firm Size and Industry Exposure

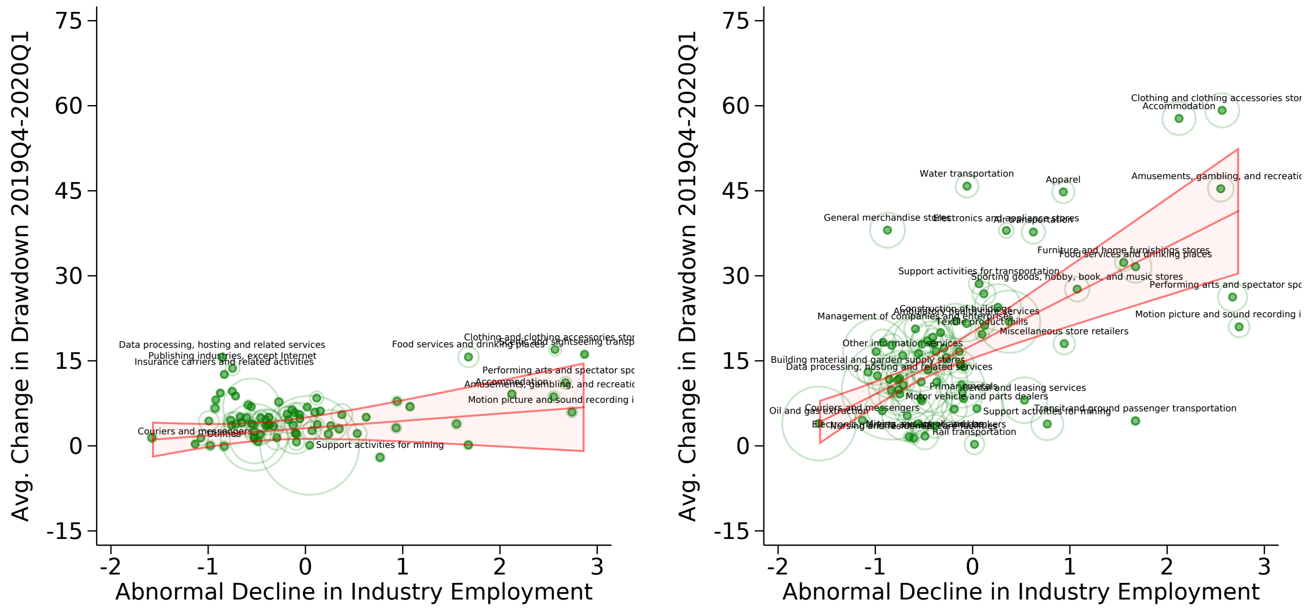
The main threat to interpreting the size gradient in drawdowns as causal evidence of loan terms mattering is that large firms may have faced larger liquidity shocks in the COVID recession. The controls for industry, state, and bond market access in Table 10 already help to alleviate this concern by removing 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 liquidity shocks varies across the size distribution.

We construct two measures of liquidity shocks. The first measure uses the percent change in national employment in the firm's three digit industry between 2019Q2 and 2020Q2 using data from the Bureau of Labor Statistics Current Employment Statistics. The change in employment provides an imperfect proxy for the demand shock to a firm, but as we will see shortly the measure lines up well with health-related risks and can be calculated for all firms. The second measure uses the percent change in national sales between 2019Q2 and 2020Q2 in the firm's three digit industry. This measure more closely accords with the theoretical notion of a liquidity shock but is available only for 13 industries included in the Census Retail Sales. For both measures, we detrend by subtracting from the 2019Q2-2020Q2 change the average Q2-to-Q2 growth rate between 2015 and 2019 and refer to the resulting measure as the abnormal employment or sales change.[16]

Figure 2 illustrates the result by plotting the industry average change in drawdown between 2019Q4 and 2020Q1 against the industry abnormal decline in employment, separately for SMEs (left panel) and firms with more than $1 billion in assets (right panel). Appendix fig. A.2 reports the corresponding plots for each of our five size categories. The employment exposure measure successfully identifies industries likely to suffer in a recession caused by risks of disease contagion, with the industries with

[15]Table A.8 reports the distribution of utilization rates in 2020Q1 and 2020Q2. Comparing to table 6, 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 $5000 million 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.

[16]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.



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

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

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

the highest exposure being scenic and sightseeing transportation, motion picture and sound recording studios, performing arts and spectator sports, clothing stores, gambling, accommodation, restaurants, and ground passenger transportation. However, SMEs in these industries draw on their credit lines at a similar rate as SMEs in less affected industries. In contrast, the right panel shows that firms with more than $1 billion in assets in highly exposed industries have drawdown rates economically and statistically much higher than do firms in less exposed industries. Thus, liquidity shocks translated into credit line drawdowns at large but not at small firms.

Table 11 reports loan-level difference-in-difference and triple-difference regressions. Column (1) gives the difference-in-difference effect of higher industry exposure on drawdowns in 2020Q1, using the employment exposure measure. In this table we standardize exposure to have unit variance, so the coefficient has the interpretation that one standard deviation higher industry exposure results in a 3.4 percentage point higher drawdown rate in 2020Q1.

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

Dependent variable	Drawdown Rate (in ppt)					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × COVID	3.4	-0.2	1.0	1.1	1.1	-1.4
	(2.2)	(2.2)	(1.4)	(1.3)	(1.2)	(1.1)
Exposure × 50-250 (in mil) × COVID		3.2**	2.0**	1.9**	1.9**	0.7
		(1.4)	(0.8)	(0.8)	(0.7)	(0.6)
Exposure × 250-1000 × COVID		4.2*	3.0*	2.9**	2.9**	1.6
		(2.1)	(1.5)	(1.4)	(1.3)	(1.2)
Exposure × 1000-5000 × COVID		7.3***	6.1***	6.1***	6.0***	4.2***
		(2.2)	(1.6)	(1.5)	(1.4)	(1.3)
Exposure × 5000- × COVID		9.3***	8.0***	7.9***	7.6***	5.1**
		(3.0)	(2.7)	(2.6)	(2.5)	(2.5)
50-250 (in mil) × COVID		4.6***	3.2***	3.2***	3.1***	0.8**
		(0.8)	(0.5)	(0.5)	(0.5)	(0.3)
250-1000 × COVID		10.3***	8.7***	8.5***	8.4***	4.0***
		(1.4)	(0.9)	(0.9)	(0.9)	(0.8)
1000-5000 × COVID		15.7***	13.8***	13.5***	13.0***	8.0***
		(1.9)	(1.2)	(1.1)	(1.1)	(0.9)
5000- × COVID		17.8***	15.1***	14.7***	14.1***	7.8***
		(2.4)	(1.8)	(1.8)	(1.7)	(1.8)
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	54078	54078	54078	54078	52683	39011
N	647169	647169	647169	647166	631307	471018
R^2	0.83	0.83	0.83	0.83	0.84	0.84

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

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

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2 and Exposure_i is the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. We restrict the sample to outstanding loans from 2017Q4 onwards. Robust standard errors are clustered at the 3-digit NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Column (2) reports the triple-difference specification:

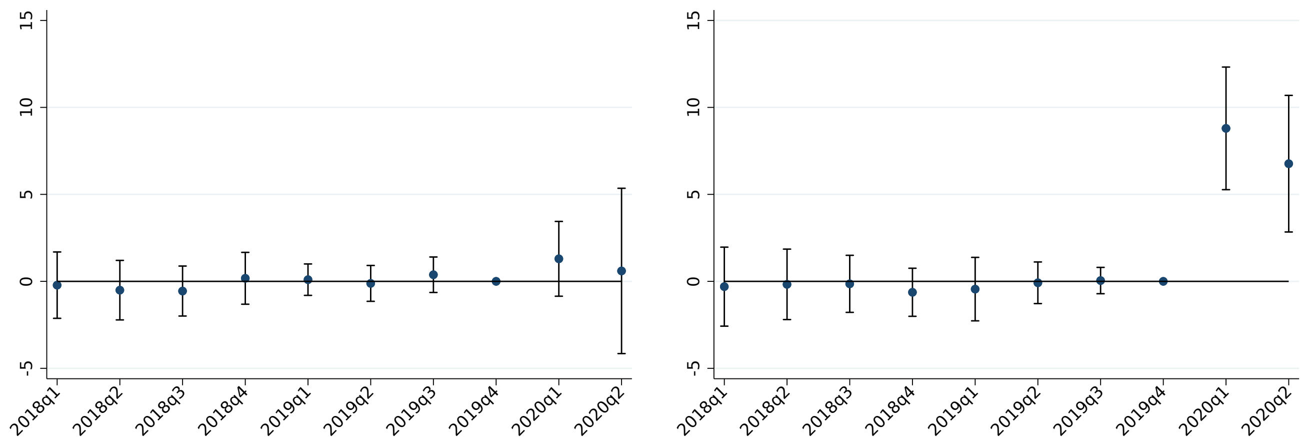
$$\text{Drawdown}_{\ell,i,t} = \alpha_\ell + \delta_t + \sum_{s \neq \{\$0-50m\}} \beta_{1,s} \left[\mathbb{I}\{\text{size class} = s\} \times \text{COVID}\right] + \beta_2 \left[\text{Exposure}_i \times \text{COVID}\right]$$
$$+ \sum_{s \neq \{\$0-50m\}} \beta_{3,s} \left[\text{Exposure} \times \mathbb{I}\{\text{size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

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 9.1 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 with a t-statistic above 3.

Figure 3 traces out the quarter-by-quarter dynamic responses to the specification in column (2) for two size classes, SMEs and firms with more than \$1 billion in assets. Appendix fig. A.3 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 an economically small and precisely estimated 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 11, columns (3) to (5) show robustness to including additional covariates. Column (3) replaces time fixed effects with bank-time fixed effects to control for differences in credit supply across banks. The triple interaction coefficients fall slightly but a large and statistically significant size gradient remains. Column (4) adds state-time fixed effects with little further impact. Column (5) adds controls for firm financials, rating, and bond market access each interacted with COVID, again with little impact.

Column (6) adds interactions of loan terms — maturity, collateral, spread, and 2019Q4 utilization — with Exposure and COVID. Appendix fig. A.1 reports the coefficients on these additional terms and shows they generally have the same sign as in table 10, with the marginal impact of Exposure on drawdown increasing with maturity and decreasing with collateral. Including these controls also reduces the size gradient in the impact of Exposure, again suggesting that restrictive loan terms inhibited the ability of firms — especially small firms — to access pre-committed credit.



(a) *<$250 million* **(b)** *>$1 billion*

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

Table 12 repeats the analysis for the retail sales exposure measure. Overall we obtain very similar results, with Exposure mattering more to larger firms. The magnitude of the gradient is similar to the employment exposure emasure but the difference loses statistical significance for the largest firms simply because the sample of firms in retail or restaurants contains many fewer very large firms.

To further rule out confounding shocks that operate at the industry level, table 13 reports instrumental variable regressions that treat the employment change in 2020 as an endogenous variable. The excluded instrument is the physical proximity requirements in the industry. Specifically, we start with the ONET survey question "How physically close to other people are you when you perform your current job?" and average the occupation-level responses within each industry using employment shares as weights.[17] To ease interpretation, we report a cross-sectional specification with the dependent variable the change in the loan's drawdown rate between 2019Q4 and 2020Q1.

The first two columns pool size classes and compare the OLS and IV coefficients. The instrument is strong, with an effective F statistic of 18.7.[18] The IV coefficient is about 25% smaller than the OLS coefficient but estimated with less precision and the data do not reject equality. The next several columns

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

[18] 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 12: ***Drawdowns by Firm Size and Exposure to COVID-19 shock: Abnormal 3-digit Industry Decline in Sales.***

Dependent variable	Drawdown Rate (in ppt)					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × COVID	11.1**	6.2*	5.0*	5.1**	4.7**	-1.1
	(4.0)	(3.5)	(2.4)	(2.2)	(2.0)	(1.4)
Exposure × 50-250 (in mil) × COVID		4.3***	3.9***	4.2***	4.4***	1.3
		(0.9)	(0.7)	(0.6)	(0.7)	(1.7)
Exposure × 250-1000 × COVID		3.0	3.5**	3.6***	3.6***	2.1
		(1.9)	(1.3)	(1.2)	(1.2)	(1.5)
Exposure × 1000-5000 × COVID		6.0	7.2**	7.2**	7.4**	4.3
		(3.5)	(2.6)	(2.6)	(2.6)	(3.1)
Exposure × 5000- × COVID		8.1	9.4	8.7	9.2	6.3
		(7.9)	(7.0)	(6.7)	(6.4)	(6.7)
50-250 (in mil) × COVID		3.8**	2.6***	2.5***	2.4***	-0.0
		(1.5)	(0.6)	(0.5)	(0.6)	(0.8)
250-1000 × COVID		7.0**	5.6***	5.0***	5.1***	0.3
		(2.5)	(1.6)	(1.6)	(1.5)	(0.7)
1000-5000 × COVID		18.9***	17.3***	16.9***	16.5***	8.8***
		(3.1)	(2.3)	(2.2)	(2.3)	(1.6)
5000- × COVID		26.1***	22.8***	23.2***	22.2***	13.3**
		(7.0)	(6.7)	(6.7)	(6.6)	(6.1)
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	13191	13191	13191	13191	12423	8639
N	157345	157345	157335	157333	146725	110437
R^2	0.81	0.81	0.82	0.82	0.83	0.81

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

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

where Drawdown$_{\ell,t}$ is the ratio of utilized over committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2 and Exposure$_i$ is the 3-digit NAICS code industry-level growth in sales between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. We restrict the sample to outstanding loans from 2017Q4 onwards. Sales data only avaiable for retail sales and restaurants. Robust standard errors are clustered at the 3-digit NAICS industry level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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

Dependent variable	Δ Drawdown$_{2020Q1-2019Q4}$ (in ppt)						
Estimation	OLS	2SLS					
Firm Size	All		<\$50	\$50-\$250	\$250-\$1000	\$1000-\$5000	>\$5000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure	4.2***	3.1	-0.6	0.5	3.9	7.9***	13.0***
	(1.5)	(2.4)	(2.3)	(2.8)	(2.4)	(2.1)	(4.5)
MP eff. F-Stat	.	18.714	18.092	18.414	15.023	16.238	11.116
No of Firms	40284	40284	26636	6668	3209	2365	1616
N	62492	62492	30257	8854	6509	8424	8448
R^2	0.013	0.012	-0.001	0.002	0.030	0.061	0.049

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

$$\Delta \text{Drawdown}_{i2020Q1-2019Q4} = \text{Exposure}_i + \epsilon_{it},$$

whereΔDrawdown$_{i2020Q1-2019Q4}$ is the difference in firm i's and Exposure$_i$ the 3-digit NAICS code industry-level growth in employment between 2019Q2 and 2020Q2 less the average Q2-to-Q2 growth in the industry between 2015 and 2019. In column (2) through (7), we instrument Exposure$_i$ with the responses to the ONET survey question "How physically close to other people are you when you perform your current job?" aggregated to the industry-level.
Standard errors are cluster at the 3-digit NAICS code industry level.

report the IV coefficient separately by firm size class. Consistent with the results in table 11, 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. The steepness of the size gradient is if anything larger in the IV analysis, although the standard errors cannot rule out a gradient similar to that with OLS.

5.3 Paycheck Protection Program

The Paycheck Protection Program (PPP) was established in the CARES Act and signed into law on March 27, 2020, with the first loans signed on April 3, 2020. The program offered term loans of an amount equal to 2.5 months payroll (capped at \$10 million) with minimum maturity of 2 (later increased to 5) years and a maximum interest rate of 4% (later set to 1%) to firms with less than 500 employees or satisfying certain other eligibility criteria. In addition, firms that maintained expenses over an 8 week period (later extended to 24 weeks) covering payroll costs, interest on mortgages, rent, and utilities in excess of the loan amount, and where payroll costs absorbed at least 75% of the loan amount (later lowered to 60%), could have the loan forgiven. Nearly 5 million borrowers received PPP loans. The Small Business Administration and Treasury Department made available a file containing the names and addresses of all PPP recipients of loans of \$150,000 or larger along with five bins of loan size (\$150-350k, \$350k-1m, \$1-2m \$2-5m, \$5-10m). We "hand" match this file to the Y-14 data using the borrower's name

Table 14: *Aggregate Drawdowns for PPP participants in $B by Firm Size, 2019Q4-2020Q2*

	Total non-PPP Credit			CL Drawdowns (pre-existing facilities)			PPP		
	2019Q4	2020Q1	2020Q2	2019Q4	2020Q1	2020Q2	max	min	N
Not classified	35.3	35.8	30.8	20.5	21.0	15.0	16.6	7.1	8343
0-50	80.1	80.8	61.8	57.7	58.3	38.8	40.2	17.1	21266
50-250	64.3	65.2	53.9	43.4	43.9	32.8	16.2	7.2	3683
250-1000	20.3	21.7	18.9	12.8	14.3	11.7	2.2	1.0	559
1000-5000	9.6	12.9	10.2	5.5	8.8	6.4	0.4	0.2	133
5000-	9.4	14.3	11.7	2.6	6.2	3.8	0.2	0.1	74
Sum	218.9	230.6	187.4	142.5	152.6	108.5	75.8	32.7	34058

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

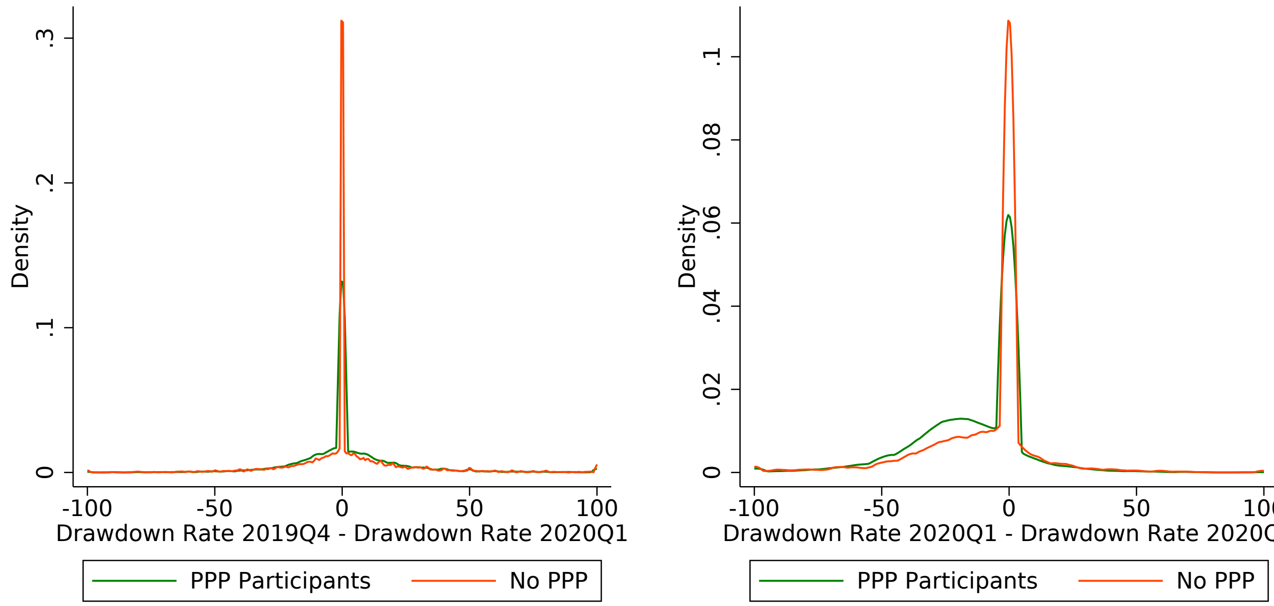
and address.

Table 14 reports the non-PPP loan balances for the firms we can identify as PPP recipients as well as the minimum and maximum PPP amounts based on the loan range. We identify 34,058 current Y-14 borrowers as PPP recipients. Consistent with the eligibility rules for program participation, 97% of the PPP loans to Y-14 borrowers with non-missing assets go to SMEs, with the vast majority going to small SMEs.

SMEs that took PPP loans had no net increase in their credit line utilization in 2020Q1, similar to other SMEs.[19] However, these firms account for a disproportionately large share of loan repayments in 2020Q2. Total credit outstanding to small SMEs fell by $21.9 billion in 2020Q2, driven by a $24.8 billion decline in utilization on existing credit lines (see table 9). Borrowers we match to the PPP file account for 79% of this $24.8 billion decline, despite accounting for less than 60% of outstanding credit at the end of 2020Q1. This likely understates the overall contribution of PPP firms, since there may be "type-II" errors of firms we fail to match because of spelling errors or other abnormalities. A similar pattern holds for large SMEs.

Figure 4 further confirms the differential repayment behavior by reporting 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.

[19] In Appendix table A.9 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.



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

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

We can use the reported loan ranges to bound the ratio of aggregate debt repayments to PPP disbursements among PPP recipients. For small SME recipients, debt repayments equal between 47% and 111% of the PPP disbursement. For large SMEs, the ratio lies between 69% and 157%, and pooling across all firms the ratio lies between 56% and 132%. 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. [20]

6 Conclusion

This paper shows that bank liquidity in bad times mostly flows toward larger rather than smaller borrowers. This is consistent with small borrowers having stricter loan terms that leave substantial discretion to the lender in providing funds. However, this does not mean that small firms never access bank liquidity, nor that large firms are always able to. In fact, using the same regulatory dataset, Brown et al. (2020) show that small firms extensively draw on their credit lines to weather idiosyncratic cash-flow shocks in "normal" times. Larger firms draw much less in spite of having cheaper and less

[20]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.

restrictive loans because their operations are more diversified and they have alternative sources of funds. Nevertheless, their credit lines are not fully committed either (Sufi, 2009). These patterns reveal that the economics behind bank liquidity provision to firms are complex, and that the tightness of financial constraints varies with the size and nature of the shock. More work is also needed to understand the implications for policy intervention. What is nevertheless clear is that credit available "on paper" in good times can severely overstate what firms can actually access in bad times.

Moreover, further efforts toward a unifying framework of loan terms is an important step to better understand credit constraints in the cross-section. Although our simple illustrative framework is able to rationalize cross-sectional differences in access to bank liquidity that we observe in the data, there are a number of forces that could be incorporated to enrich the analysis. Existing theories focusing on collateral, maturity, or covenants have highlighted trade-offs that we abstract from. For instance, we do not explicitly discuss the potential effects of borrowers' misbehavior or of the presence of multiple creditors. This is because we primarily focus on the effect of a large external shock on small borrowers, which tend to have concentrated creditors. Nevertheless, it is well-established that credit lines are prone to abuse because of their flexibility. Acharya et al. (2014) proposed a theory of credit line as monitored liquidity insurance to prevent borrowers from engaging in illiquidity-seeking after the loan agreement is in place. Moreover, lenders have additional incentives to prevent draw-downs if they believe funds will be used to repay other creditors.

References

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Chen, B., S. Hanson, and J. Stein (2017, September). The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets. Working Paper 23843, National Bureau of Economic Research.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

APPENDIX

Appendix A: Proofs

Appendix B: Supplementary Figures

Appendix C: Supplementary Tables

A Proofs

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

B Supplementary Figures

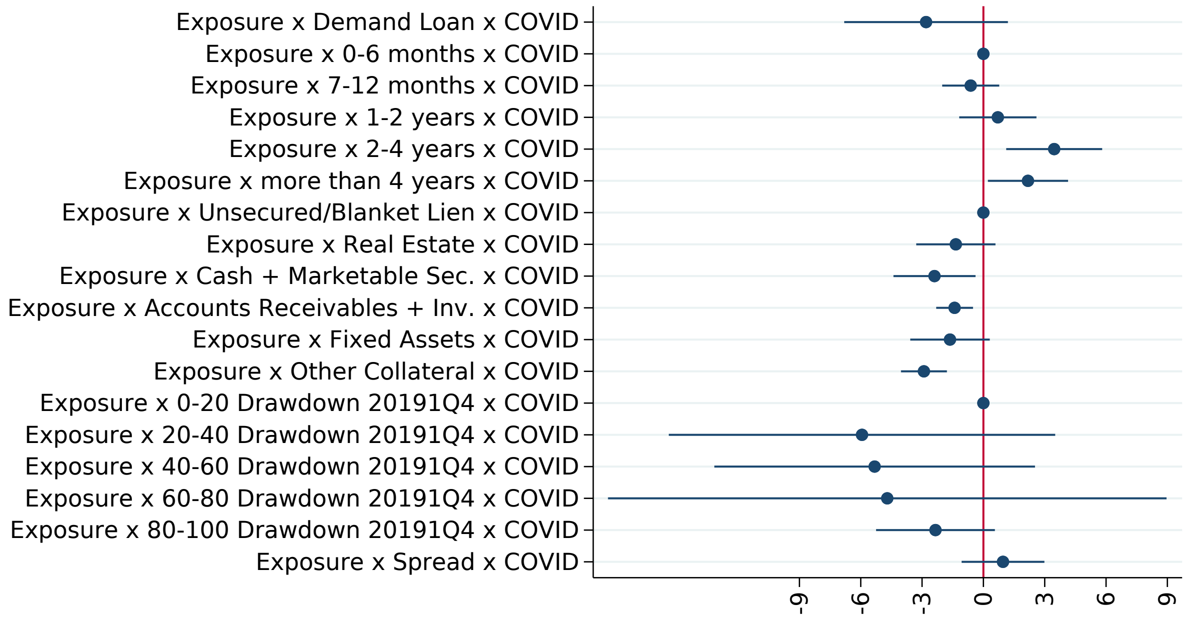
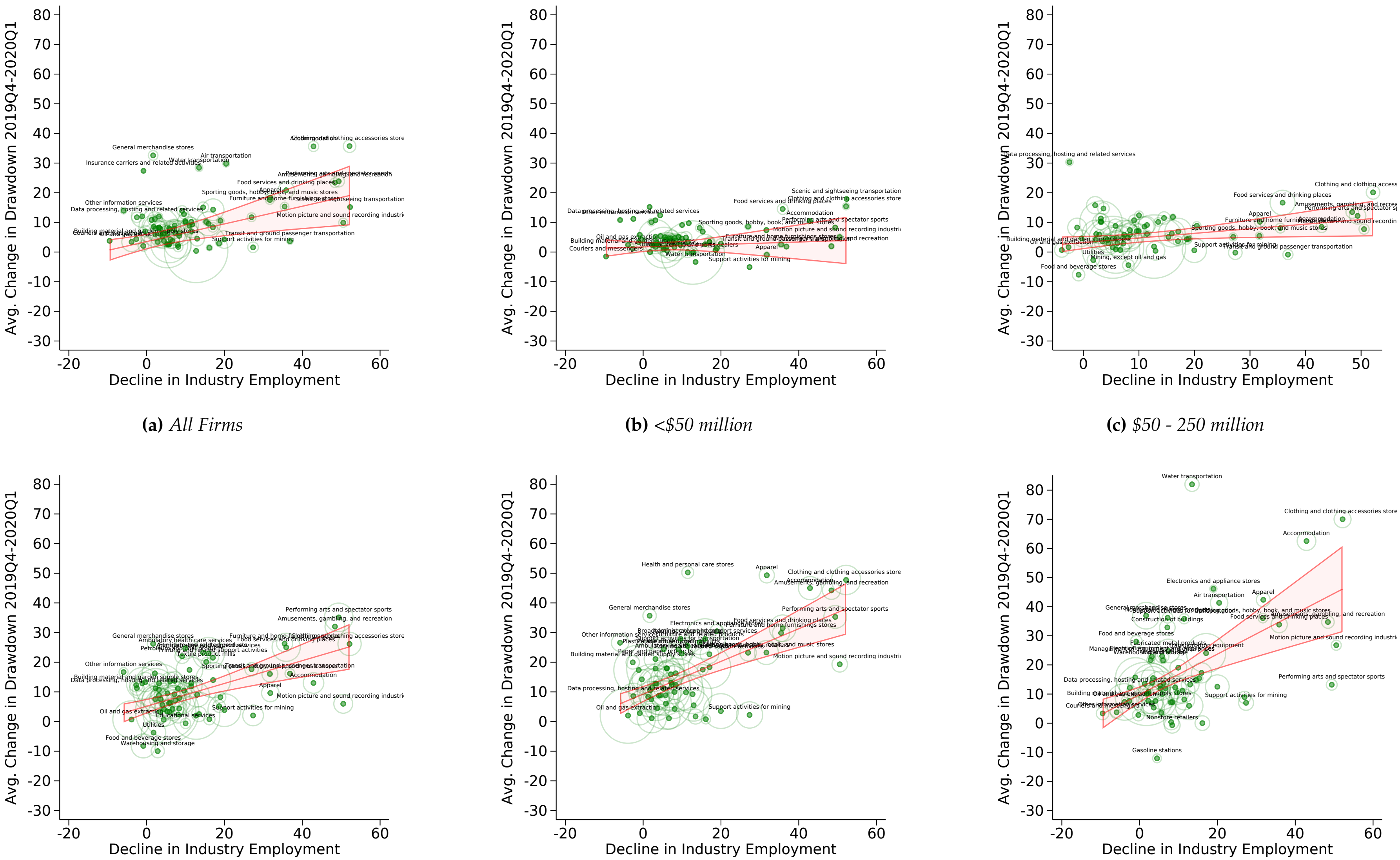


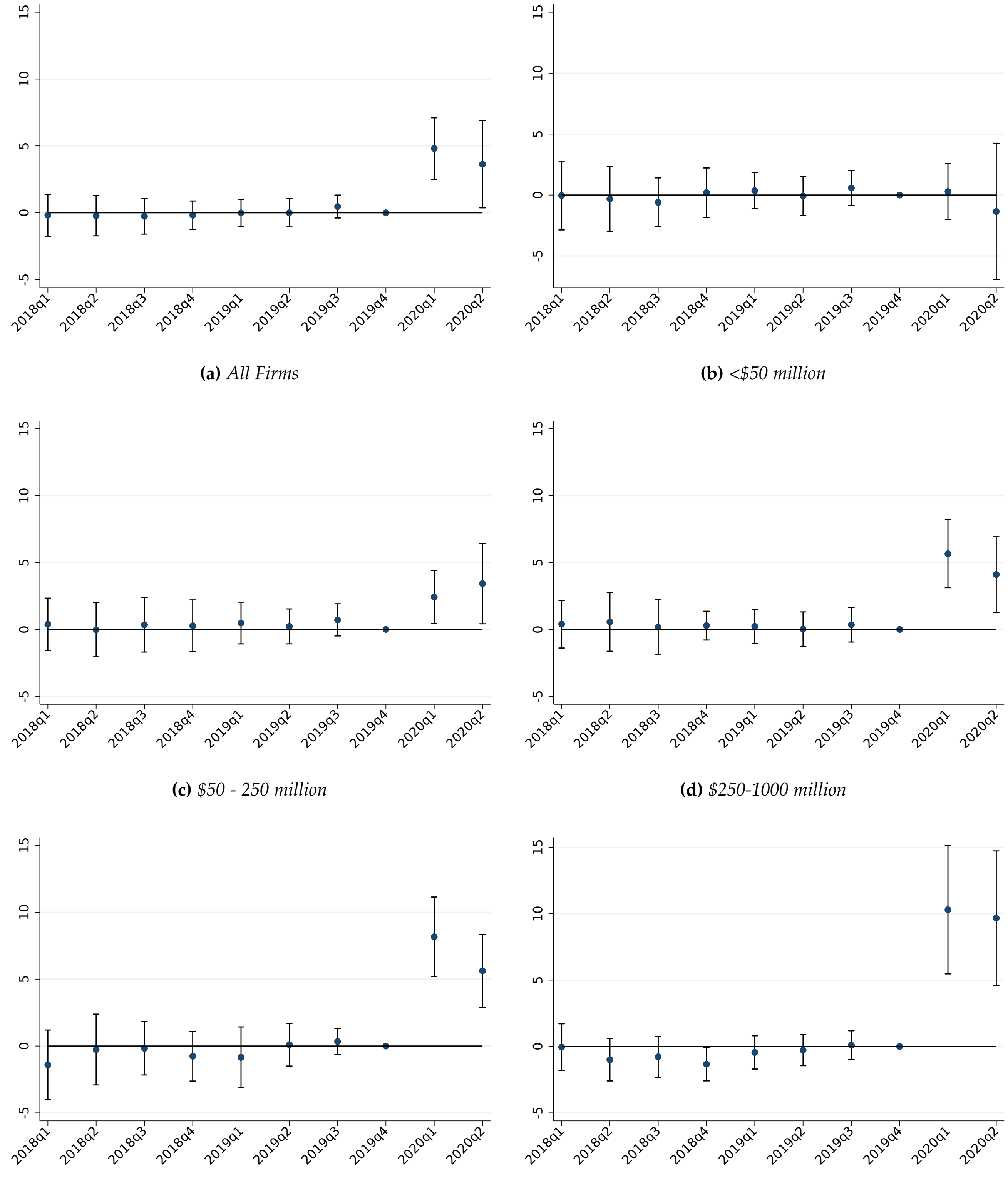
Figure A.1: ***Drawdown by Loan Terms and COVID Exposure.*** *Reporting additional coefficients omitted in column (6) of Table 11 that result from estimating Equation* (3)*.*



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

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

Figure A.2: ***Industry COVID Exposure and Credit Line Drawdowns by Firm Size.*** *3-digit NAICS code industry-level. Average change in credit line drawdown from 2019Q4 through 2020Q1. Employment growth between 2019Q2 and 2020Q2 less the Q2-to-Q2 average between 2015 and 2019. Linear fit with industries weighted by number of firms per industry. Data restricted to industries with at least 10 firms per firm size category. Perimeter of hollow circles indicate relative industry size by number of firms reporting in the Y14.*



(a) *All Firms*

(b) *<$50 million*

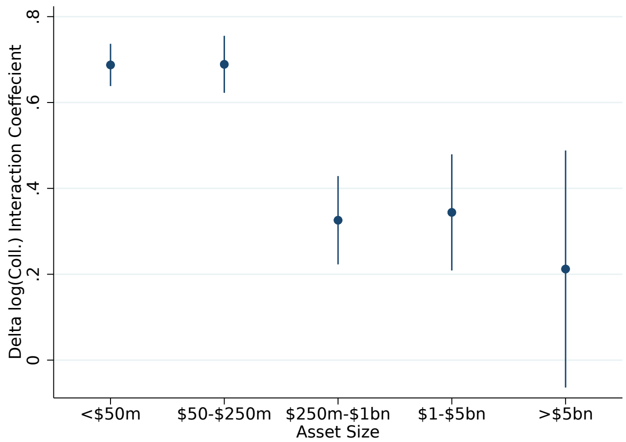
(c) *$50 - 250 million*

(d) *$250-1000 million*

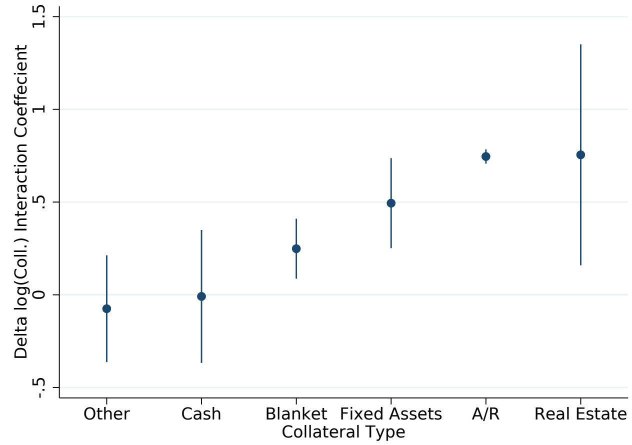
(e) *$1-5 billion*

(f) *>$5 billion*

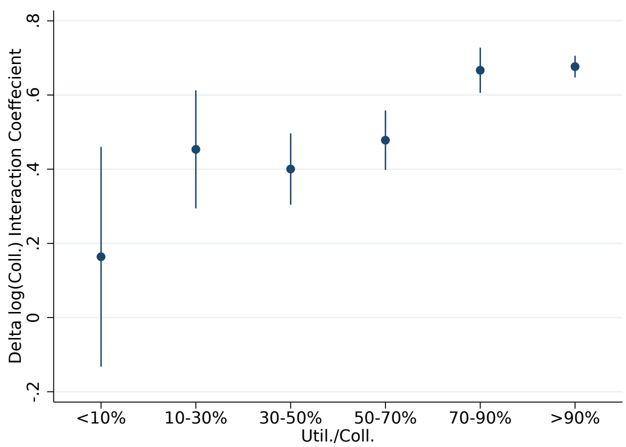
Figure A.3: ***Industry COVID Exposure and Credit Line Drawdowns by Firm Size.*** *The figure plots the sequence of coefficients $\{\beta_t\}$ obtained from estimating $Drawdown_{\ell,t} = \alpha_\ell + \delta_t + \beta_t \times Exposure_i + \epsilon_{\ell,i,t}$, where $Drawdown_{\ell,t}$ is the ratio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



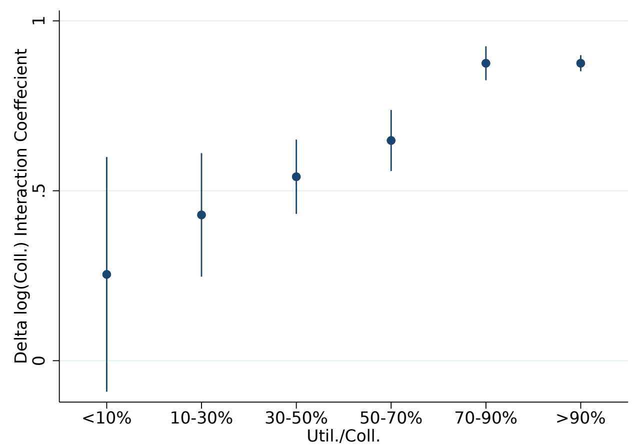
(a)



(b)

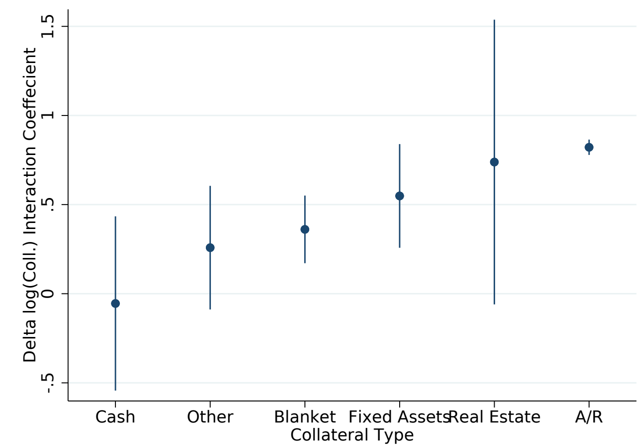


(c)

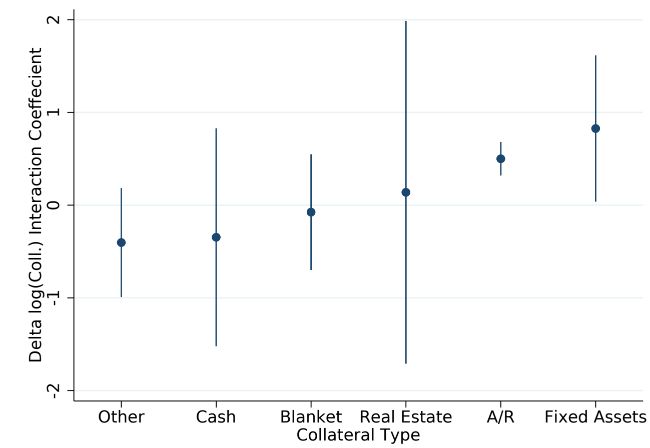


(d)

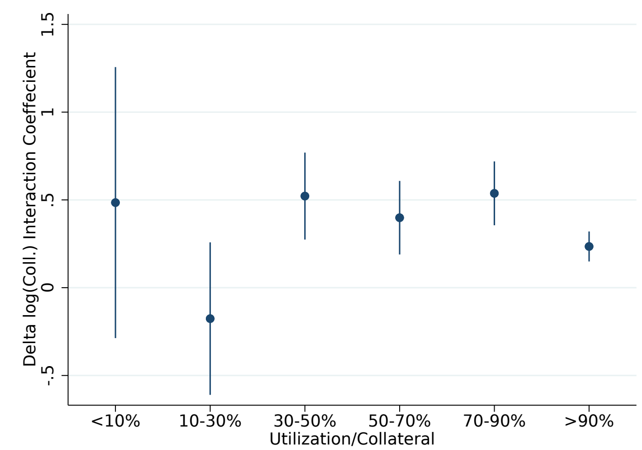
Figure A.4: *The figures above plot coefficients estimated using a loan-level panel regression of the change in the log of utilization on the change in log collateral values in the presence of various controls, see Eq. 1. Indicator interactions are used to recover elasticities for sub-samples of loans. Controls include bank-time, industry-time, and rating-time fixed effects, as well as uninteracted indicator variables and the change in the log of commitment size. The sample period is 2015Q1 to 2020Q1. Figures plot the elasticity of utilization to collateral, β, for each sub-sample interaction and the 95% confidence interval. Panel (a) interacts plots elasticities by firm size bin, Panel (b) by collateral type, and Panels (c) and (d) with the percent of utilization relative to collateral value. Panel (d) restricts the sample to loans collateralized by accounts receivable. Standard errors are clustered by firm.*



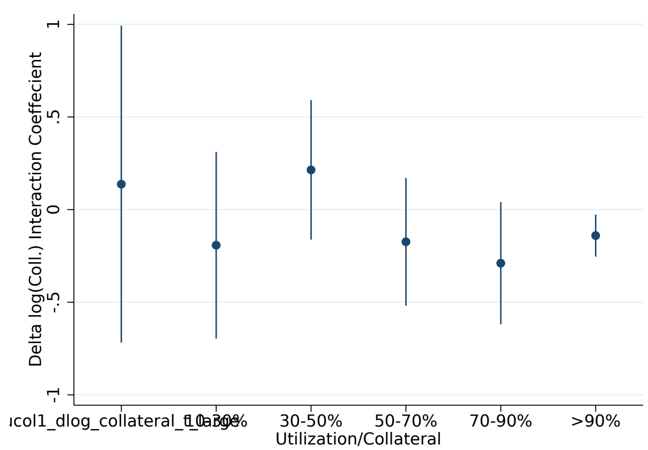
(a)



(b)



(c)



(d)

Figure A.5: *Regression coefficients are estimated using a loan-level panel regression of the change in the log of utilization on the change in log commitments and collateral values in the presence of various controls:* $\Delta \log(utilization_{it}) = \Pi(Type_{it} \times \Delta \log(collateral_{it})) + \Gamma(Type_{it} \times \Delta log(commitment_{it})) + \Theta \mathbf{X_{it}} + \varepsilon_{it}$*, where i denotes a loan and t time. Type interactions estimate the sensitivity of utilization to commitment and collateral values by type indicator (e.g. collateral type, size category, etc.). Controls,* $\mathbf{X_{it}}$*, include bank-time, industry-time, and rating-time fixed effects, as well as uninteracted Type indicator variables. The sample period is 2015Q1 to 2020Q1. Figures plot the vector of coefficients,* Γ*, on the log change in collateral values and the 95% confidence interval. Panel (a) interacts with collateral type and SME size, Panel (b) with collateral type and large size, Panel (c) and (d) interact with the percent of utilization relative to collateral value and SME and Large firms respectively. Standard errors are clustered by firm.*

C Supplementary Tables

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

Dataset	2019q4				2020q1				2020q2			
Description	Comm.	Util.	No. Banks	No. Obs	Comm.	Util.	No. Banks	No. Obs	Comm.	Util.	No. Banks	No. Obs
Y-9C Total	4,608	2,254	350	0	4,627	2,565	349	0	4,833	2,573	345	0
Y-9C Ag.	46	46	247	0	44	44	245	0	46	46	244	0
Y-9C C&I	3,805	1,705	345	0	3,826	2,015	345	0	4,039	2,022	341	0
Y-9C CRE	631	377	340	0	633	381	340	0	626	382	337	0
Y-9C Oth. Leases	126	126	120	0	125	125	129	0	123	123	129	0
Y-9C C&I > 1 Mil.	3,533	1,449	347	0	3,552	1,753	346	0	3,611	1,623	343	0
Y-9C CRE > 1 Mil.	496	242	341	0	501	249	341	0	494	250	338	0
Y-9C Total Balanced	3,536	1,557	29	0	3,533	1,829	29	0	3,608	1,733	29	0
Y-9C Ag. Balanced	13	13	22	0	12	12	22	0	11	11	22	0
Y-9C C&I Balanced	3,124	1,274	29	0	3,125	1,549	29	0	3,207	1,457	29	0
Y-9C CRE Balanced	298	169	29	0	298	169	29	0	293	169	29	0
Y-9C Oth. Leases Balanced	101	101	26	0	99	99	26	0	96	96	26	0
Y-9C C&I > 1 Mil. Balanced	2,959	1,109	29	0	2,959	1,383	29	0	2,961	1,211	29	0
Y-9C CRE > 1 Mil. Balanced	249	119	29	0	249	121	29	0	246	122	29	0
Y-14Q Original Aggregate	4,613	1,997	32	270748	4,639	2,348	32	266749	4,624	2,073	32	267384
Y-14Q Final Aggregate	3,150	1,270	29	204878	3,160	1,539	29	201665	3,114	1,317	29	202728
Y-14Q Ag. Loans	14	8	20	2218	14	7	20	2114	14	7	20	2043
Y-14Q C&I Loans	2,955	1,094	29	159093	2,967	1,364	29	156309	2,917	1,140	29	155322
Y-14Q CRE Loans	122	114	28	33196	123	116	28	33201	128	121	28	35413
Y-14Q Oth. Leases	59	54	25	10371	57	52	25	10041	55	50	25	9950

Notes: This table reports the aggregate amount of committed and utilized bank credit in the FR-Y9C and the FR-Y14 H1 in the quarter reported in the header. We apply several sample selections such as excluding loans less than a million, only banks that report Y14 data from 2019Q4 through 2020Q2 consistently, loans to U.S. Corporations, and other data adjustments.

Table A.2: ***Remaining Maturity by Facility Type and Firm Size Category for Loans Outstanding between 2017Q1-2019Q4***

Loan Due:	Demand	Jan	Feb	Mar	Q2	Q3-Q4	2021	2022-24	Later	Obs.
Assets (mil.)										
Panel A1: Revolving Credit Lines for Private Firms										
0-50	.29	.04	.044	.049	.17	.23	.11	.04	.022	368698
50-250	.16	.023	.023	.029	.083	.16	.19	.22	.12	102201
250-1000	.11	.0077	.01	.012	.039	.083	.16	.37	.22	54781
1000-5000	.091	.0039	.0049	.0061	.02	.045	.14	.44	.28	38510
5000-	.099	.0081	.007	.0096	.029	.056	.11	.41	.3	19052
Panel A2: Revolving Credit Lines for Public Firms										
0-50	0	.032	.047	.061	.12	.22	.22	.16	.052	833
50-250	0	.01	.011	.012	.033	.092	.2	.37	.21	3033
250-1000	0	.0024	.0035	.0046	.012	.039	.15	.43	.32	15518
1000-5000	0	.0018	.0016	.0029	.0085	.024	.11	.46	.34	46753
5000-	0	.0076	.0078	.0094	.022	.049	.1	.42	.36	65072
Panel B1: Term Loans for Private Firms										
0-50	.0017	.0067	.0066	.0089	.02	.038	.072	.24	.62	181007
50-250	.00075	.0056	.0056	.0072	.019	.042	.11	.36	.47	82683
250-1000	.0017	.0038	.0046	.006	.015	.041	.13	.39	.42	34876
1000-5000	0	.0036	.0055	.0076	.018	.047	.11	.38	.45	14280
5000-	.00013	.018	.013	.013	.029	.059	.12	.38	.39	7939
Panel B2: Term Loans for Public Firms										
0-50	0	.015	.0077	.0077	.027	.058	.13	.34	.45	260
50-250	0	.0074	.01	.0029	.022	.063	.16	.45	.31	1360
250-1000	0	.0013	.0011	.0029	.0073	.032	.13	.42	.43	4543
1000-5000	0	.0023	.0023	.0039	.0097	.026	.11	.48	.38	15132
5000-	0	.014	.01	.014	.039	.092	.16	.39	.3	16386

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

Table A.3: ***Collateral Use by Facility Type and Firm Size Category, 2017Q1-2019Q4***

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets (mil.)								
Panel A1: Revolving Credit Lines for Private Firms								
0-50	.02	.011	.49	.038	.043	.37	.037	260525
50-250	.026	.023	.45	.062	.072	.28	.09	85591
250-1000	.015	.036	.38	.06	.091	.24	.18	48548
1000-5000	.0057	.039	.35	.049	.11	.17	.28	34992
5000-	.0017	.024	.18	.033	.089	.12	.56	17171
Panel A2: Revolving Credit Lines for Public Firms								
0-50	.014	.061	.47	.027	.069	.33	.034	772
50-250	.0025	.031	.45	.047	.08	.31	.082	2813
250-1000	.0016	.047	.39	.044	.094	.26	.17	14356
1000-5000	.0017	.047	.28	.038	.1	.18	.35	43463
5000-	.00072	.019	.079	.012	.067	.06	.76	61538
Panel B1: Term Loans for Private Firms								
0-50	.44	.0058	.13	.14	.027	.24	.026	180699
50-250	.23	.012	.15	.32	.044	.22	.033	82621
250-1000	.14	.022	.14	.37	.053	.21	.065	34815
1000-5000	.12	.024	.14	.25	.07	.21	.19	14280
5000-	.036	.024	.1	.21	.095	.19	.34	7938
Panel B2: Term Loans for Public Firms								
0-50	.2	.015	.073	.12	.065	.51	.012	260
50-250	.057	.036	.23	.14	.098	.41	.019	1360
250-1000	.021	.054	.28	.12	.1	.34	.09	4543
1000-5000	.0069	.05	.2	.12	.087	.24	.3	15131
5000-	.0056	.023	.098	.13	.069	.13	.55	16386

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

Table A.4: ***Interest Rates by Facility Type and Firm Size Category between 2017Q1-2019Q4***

Interest in bp	0 -100	100-200	200-300	300-400	400 -500	500 -600	>600	Obs.
Assets (mil.)								
Panel A1: Revolving Credit Lines for Private Firms								
0-50	.018	.0057	.066	.25	.38	.22	.062	249355
50-250	.048	.018	.16	.36	.24	.097	.08	69482
250-1000	.06	.022	.16	.33	.22	.11	.1	37587
1000-5000	.087	.017	.17	.33	.22	.1	.076	25191
5000-	.18	.049	.22	.34	.12	.058	.039	8274
Panel A2: Revolving Credit Lines for Public Firms								
0-50	.038	.0064	.062	.29	.32	.14	.13	471
50-250	.06	.0077	.11	.27	.25	.15	.16	2081
250-1000	.079	.012	.15	.32	.24	.1	.097	9912
1000-5000	.1	.029	.2	.37	.18	.068	.054	27671
5000-	.2	.042	.2	.37	.11	.044	.038	18939
Panel B1: Term Loans for Private Firms								
0-50	.017	.0028	.064	.32	.44	.13	.027	180998
50-250	.021	.008	.14	.39	.3	.087	.054	82665
250-1000	.026	.013	.18	.37	.25	.084	.078	34847
1000-5000	.04	.02	.2	.41	.21	.067	.047	14280
5000-	.058	.031	.24	.45	.17	.03	.018	7907
Panel B2: Term Loans for Public Firms								
0-50	.042	0	.1	.25	.34	.15	.11	260
50-250	.024	.0037	.099	.26	.22	.24	.16	1360
250-1000	.057	.0064	.13	.32	.29	.12	.083	4543
1000-5000	.049	.024	.22	.45	.21	.035	.022	15130
5000-	.1	.028	.26	.43	.12	.033	.014	16383

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

Table A.5: *Distribution of Collateral Use by Industry and Facility Type, December 31, 2019*

Collateral Type	Real Estate	Cash	AR & Inventory	Fixed Assets	Other	Blanket Lien	Unsecured	Obs.
Assets (mil.)								
				Panel A: Revolving Credit Lines				
11: Agriculture, Forestry, Fishing, Hunting	.017	.016	.45	.062	.081	.29	.088	1089
21: Mining, Quarrying, Oil, Gas.	.0079	.044	.33	.054	.23	.12	.21	1516
22: Utilities	.0015	.025	.036	.014	.075	.069	.78	1378
23: Construction	.012	.024	.33	.059	.052	.4	.13	3283
31-33: Manufacturing	.01	.02	.35	.037	.063	.27	.25	13118
42: Wholesale Trade	.011	.012	.5	.022	.039	.33	.094	8576
44-45: Retail Trade	.029	.0072	.67	.012	.027	.15	.11	6111
48-49: Transportation and Warehousing	.019	.016	.27	.1	.081	.27	.25	2043
51: Information	.0048	.036	.23	.016	.12	.31	.28	1666
52: Finance and Insurance	0	.069	.086	0	.53	.052	.28	58
53: Real Estate and Rental and Leasing	.034	.059	.22	.13	.072	.13	.35	1287
54: Professional, Scientific, and Technical Services	.0042	.021	.38	.012	.058	.4	.13	3782
55: Management of Companies and Enterprises	.015	.15	.16	.0073	.022	.34	.31	137
56: Administrative ...	.0096	.032	.35	.03	.082	.4	.11	1668
61: Educational Services	.042	.014	.28	.014	.2	.39	.056	71
62: Health Care and Social Assistance	.042	.03	.33	.032	.076	.4	.092	792
71: Arts, Entertainment, and Recreation	.042	.062	.24	.12	.17	.28	.093	551
72: Accommodation and Food Services	.055	.045	.17	.039	.21	.31	.17	919
81: Other Services	.039	.054	.28	.03	.057	.36	.17	334
92: Public Administration	0	0	0	0	.25	.5	.25	4
								0
				Panel B: Term Loans				
11: Agriculture, Forestry, Fishing, Hunting	.2	.021	.15	.42	.087	.091	.028	287
21: Mining, Quarrying, Oil, Gas.	.08	.0089	.23	.34	.077	.17	.098	338
22: Utilities	.059	.059	.077	.2	.056	.15	.4	287
23: Construction	.22	.0098	.1	.44	.028	.17	.038	1626
31-33: Manufacturing	.21	.014	.14	.24	.044	.23	.12	7157
42: Wholesale Trade	.36	.0081	.13	.17	.035	.24	.059	3203
44-45: Retail Trade	.47	.0047	.26	.044	.013	.17	.049	4679
48-49: Transportation and Warehousing	.12	.0022	.057	.66	.037	.079	.04	2786
51: Information	.11	.024	.15	.13	.1	.35	.14	892
52: Finance and Insurance	.42	0	.044	.22	.044	.18	.089	45
53: Real Estate and Rental and Leasing	.53	.0083	.032	.22	.032	.13	.053	3362
54: Professional, Scientific, and Technical Services	.2	.012	.17	.13	.052	.36	.083	1600
55: Management of Companies and Enterprises	.48	.0045	.05	.14	.014	.25	.073	220
56: Administrative ...	.21	.0081	.16	.22	.037	.31	.061	737
61: Educational Services	.53	.02	.059	.079	.02	.26	.03	101
62: Health Care and Social Assistance	.33	.013	.14	.11	.055	.31	.062	1261
71: Arts, Entertainment, and Recreation	.36	.04	.087	.27	.058	.17	.021	624
72: Accommodation and Food Services	.19	.018	.065	.051	.075	.58	.024	2075
81: Other Services	.58	.0091	.048	.075	.021	.21	.062	438
92: Public Administration	.63	0	0	0	0	.38	0	8
								0

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

Table A.6: ***Collateral Usage in Credit Lines by Firms Size and Industry.***

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

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

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

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

Table A.7: ***Pricing of Non-Revolving Credit Lines and Capitalized Lease Obligations..***

Dependent variable	Interest Rate (in bp)										
Sample	Non-Revolving Credit Lines						Capitalized Lease Oblg.				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
50-250 (in mil)	-16.2***	-15.9***	-16.0***	-14.4***	-11.7***	-11.7***	-38.6***	-35.2***	-29.4***	-28.7***	-28.1***
	(3.8)	(3.7)	(3.7)	(3.3)	(3.4)	(3.4)	(7.6)	(7.2)	(7.0)	(6.5)	(6.6)
250-1000	-7.2	-12.1*	-18.3**	-7.9	-3.5	-3.5	-42.3***	-37.2***	-26.4***	-25.0***	-23.6**
	(6.0)	(5.8)	(5.9)	(4.6)	(4.9)	(4.9)	(9.3)	(8.3)	(7.7)	(7.3)	(7.4)
1000-5000	-75.1***	-86.0***	-94.0***	-68.0***	-54.9***	-55.0***	-63.3***	-56.9***	-41.1***	-42.0***	-40.4***
	(5.8)	(5.1)	(5.2)	(4.5)	(5.2)	(5.3)	(7.7)	(8.3)	(8.1)	(7.8)	(8.1)
5000-	-117.4***	-124.2***	-125.0***	-85.8***	-67.9***	-68.0***	-72.9***	-70.3***	-53.3***	-48.3***	-46.3***
	(4.9)	(5.3)	(5.4)	(5.4)	(6.8)	(6.8)	(12.2)	(9.4)	(8.1)	(7.7)	(8.1)
Reference-Rate-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Bank-Time FE	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Rating-Time FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes
Firm Financial Controls	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes
Loan Terms Controls	No	No	No	No	Yes	Yes	No	No	No	No	Yes
Drawdown	No	No	No	No	No	Yes	Yes	No	No	No	Yes
No of Firms	7332	7281	7263	7000	6997	6997	2938	2920	2906	2885	2885
N	12215	12149	12119	11787	11778	11778	8647	8603	8575	8540	8540
R^2	0.326	0.393	0.458	0.560	0.568	0.568	0.127	0.253	0.363	0.437	0.445

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

$$\text{Interest}_{\ell,t} = \delta_t + \sum_{s\neq\{\$0-50m\}} \beta_{1,s}\mathbb{I}\{\text{size class} = s\} + \beta_2 \frac{\text{Debt}}{\text{Assets}}_{i,t-1} + \beta_3 \frac{\text{Operating Income}}{\text{Interest Expense}}_{i,t-1} + \beta_4 \frac{\text{Net Income}}{\text{Assets}}_{i,t-1}$$
$$+ \sum_{m\neq\{0-6\text{ months}\}} \beta_{5,m}\mathbb{I}\{\text{maturity class} = m\} + \sum_{j\neq\{\text{Unsecured/BL}\}} \beta_{6,j}\mathbb{I}\{\text{collateral class} = j\} + \beta_7\text{LoanSize}_{\ell,t} + \beta_7\text{Drawdown}_{\ell,t}$$
$$+ \text{Reference-Rate-Time FE} + \text{Industry-Time FE} + \text{Bank-Time FE} + \text{Rating-Time FE} + \epsilon_{\ell,t}$$

where $\text{Interest}_{\ell,i,b,t}$ is the interest on facility ℓ from bank b to firm i at time t. We group the firms in 5 size class categories (by asset size in \$million), and consider 6 maturity class categories (demand loans, 0-6 months, 6-12 months, 1-2 years, 2-4 years, more than 4 years) and 6 types of collateral classes (real restate, marketable securities, accounts receivables and inventory, fixed assets, other, and unsecured or blanket lien). $\text{LoanSize}_{\ell,t}$ is the log of the committed loan limit. We restrict the sample to originations and renewals between 2015Q1 and 2019Q4.
Robust standard errors are clustered at the firm level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A.8: ***Drawdown of Revolving Credit Lines by Firm Size, 2020Q1 and 2020Q2***

	Utilization/Commitment						
Assets (mil.)	$< 10\%$	$10-$ 30%	$30-$ 50%	$50-$ 70%	$70-$ 90%	$> 90\%$	Obs.
Panel A: 2020Q1							
0-50	.3	.086	.12	.16	.14	.19	30582
50-250	.31	.1	.12	.16	.14	.16	8791
250-1000	.28	.11	.15	.16	.15	.15	5950
1000-5000	.29	.16	.14	.14	.12	.15	7273
5000-	.52	.12	.1	.082	.047	.13	7617
Panel B: 2020Q2							
0-50	.41	.11	.16	.12	.068	.12	29549
50-250	.4	.12	.14	.13	.085	.13	8622
250-1000	.35	.12	.16	.14	.093	.14	6090
1000-5000	.39	.15	.14	.11	.073	.13	7378
5000-	.66	.088	.063	.044	.026	.12	8060

Notes: The table reports the mean fraction drawn credit as share of total commitments values.

Table A.9: ***PPP Participation and COVID Exposure and Loan Terms.***

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

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

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

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

Table A.10: ***Drawdowns by Exposure to COVID-19 shock: State-level Death Rate.***

Dependent variable	Drawdown Rate (in ppt)					
Exposure	Deathrate					
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × COVID	0.9***	1.0***	0.8***	0.6***	0.6***	1.2***
	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.5)
Exposure × 50-250 (in mil) × COVID		-0.2	-0.3	-0.2	-0.3	-0.4**
		(0.3)	(0.2)	(0.2)	(0.2)	(0.2)
Exposure × 250-1000 × COVID		0.0	0.1	-0.1	-0.0	0.0
		(0.5)	(0.5)	(0.3)	(0.3)	(0.3)
Exposure × 1000-5000 × COVID		0.3	0.3	0.3	0.2	-0.1
		(0.3)	(0.4)	(0.3)	(0.3)	(0.4)
Exposure × 5000- × COVID		-0.6	-0.4	-0.4	-0.3	-0.3
		(0.8)	(0.7)	(0.7)	(0.7)	(0.8)
50-250 (in mil) × COVID		3.9***	2.9***	1.8***	1.9***	0.7
		(0.5)	(0.4)	(0.4)	(0.4)	(0.5)
250-1000 × COVID		9.4***	8.1***	5.9***	5.9***	3.3***
		(0.5)	(0.5)	(0.5)	(0.5)	(0.6)
1000-5000 × COVID		13.5***	11.9***	9.6***	9.4***	6.7***
		(0.6)	(0.6)	(0.6)	(0.8)	(0.7)
5000- × COVID		14.5***	12.4***	9.7***	9.5***	5.8***
		(1.3)	(1.1)	(1.2)	(1.4)	(1.3)
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
Industry-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	51347	51347	51347	51313	49750	36979
N	581775	581775	581775	581306	560984	419372
R^2	0.83	0.83	0.83	0.84	0.84	0.84

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

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

where $\text{Drawdown}_{\ell,t}$ is the ratio of utilized over committed credit, COVID is an indicator variable for 2020Q1 and 2020Q2 and Exposure_i is state-level excess death rate. We restrict the sample to outstanding loans from 2017Q4 onwards. Sales data only available for retail sales and restaurants.
Robust standard errors are clustered at the state level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.