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Dynamic credit constraints: theory and evidence from credit lines

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Abstract

We use a comprehensive Swedish credit register to document that firms across the size distribution have access to substantial borrowing capacity via credit lines. However, most firms choose not to use all available credit, even though interest rates are low compared to their return on equity. The low utilization of credit is consistent with a theoretical model in which utilization rates decrease with both real and financial uncertainty. We estimate the model structurally at the firm level and find that *financial* uncertainty driven by liquidity shocks is much more important than *real* uncertainty driven by cash flow shocks for explaining the low utilization of credit.

Keywords: Credit constraints; banks; uncertainty; credit lines; precautionary behavior.

JEL: D22; E44; G21; G32.

Non-technical Summary

Credit constraints—the inability of firms to raise sufficient amounts of credit at a reasonable cost—play an important role in modern economic models of both short-term fluctuations and long-term growth.

In this paper, we use new data from a comprehensive Swedish credit registry to better understand the extent to which firms are credit constrained. Our motivation for doing so is that some aspects of the data may be difficult, at first sight, to reconcile with the view that tight credit constraints are widespread, especially among small firms. We document that a majority of non-financial firms—from micro-sized enterprises to the largest firms in the economy—have access to credit lines that allow them to increase borrowing today at a cost that is low compared to their return on equity, but they choose not to use them. This finding holds even after we account for the seasonality of credit demand and for typical covenants that may restrict the actual ability of firms to draw on their credit lines.

The observation that many firms choose not to use all the credit available to them may indicate that they are not credit constrained. Such an interpretation follows from a static view of credit constraints, according to which a firm is unconstrained if it is able to borrow more today at a reasonable cost, but chooses not to do so. Another interpretation, however, is that the low utilization of available credit indicates that firms face tight *dynamic* credit constraints, supporting the view that credit constraints are widespread in the corporate sector. Distinguishing between these potential explanations for the overall low credit utilization observed in the data is critical for understanding if, and how, credit constraints affect firms and thereby the broader economy.

To this end, we introduce a simple dynamic model in which a firm's current financial decisions affect its financial condition in the future. The purpose of the model is not to propose a new theory of the financial decisions of firms, as it simply synthesizes elements from existing theories, but rather to help us delineate a dynamic concept of credit constraints and interpret what we observe in the data.

While it is straightforward to define a dynamic concept of credit constraints in the context of a theoretical model, it is difficult to measure it empirically. This is because we do not directly

observe how current borrowing affects the expected marginal cost of future borrowing. In the data, we typically observe current prices and quantities, but not expectations of the future cost of illiquidity. However, we can construct these expectations indirectly using the quantitative predictions of the model.

The model delivers two main predictions. First, dynamically constrained firms decrease borrowing in response to increases in uncertainty about future access to credit. Second, the borrowing of a dynamically constrained firm responds to changes in the credit limit even if its borrowing constraint is slack prior to the limit change. Taking these predictions to the data enables us to assess whether tight dynamic constraints are likely to be an explanation for the low credit utilization observed in the data. We empirically confirm these predictions and conclude that firms are indeed credit constrained, in a dynamic sense.

1 Introduction

Credit constraints—the inability of firms to raise sufficient amounts of credit at a reasonable cost—play an important role in modern economic models of both short-term fluctuations and long-term growth.[1] The prominence of credit constraints in these models is motivated by a large body of empirical evidence showing that cross-sectional and time-series variations in credit supply affect firms' real economic activity. This is consistent with the notion that many firms face binding credit constraints.[2] The evidence also indicates that tight credit constraints are particularly prevalent in certain groups of firms, for example, among small firms (Gertler and Gilchrist, 1994; Campello, Graham and Harvey, 2010), young firms (Cloyne et al., 2023; Davis and Haltiwanger, 2024), and firms with few pledgeable assets (Almeida and Campello, 2007).

In this paper, we use new data from a comprehensive Swedish credit registry to better understand the extent to which firms are credit constrained. Our motivation for doing so is that some aspects of the data may be difficult, at first sight, to reconcile with the view that tight credit constraints are widespread, especially among small firms. We document that a majority of non-financial firms—from micro-sized enterprises to the largest firms in the economy—have access to credit lines that allow them to increase borrowing today at a cost that is low compared to their return on equity, but they choose not to use them. This finding holds even after we account for the seasonality of credit demand and for typical covenants that may restrict the actual ability of firms to draw on their credit lines.

The observation that many firms choose not to use all the credit available to them may indicate that they are not credit constrained. Such an interpretation follows from a static view of credit constraints, according to which a firm is unconstrained if it is able to borrow more today at a reasonable cost, but chooses not to do so. Another interpretation, however, is that the low utilization of available credit indicates that firms face tight *dynamic* credit constraints, supporting

[1]For theories of business cycles featuring credit constraints, see, for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Gertler and Kiyotaki (2010), and Brunnermeier and Sannikov (2014). Theories of long-run growth and development based on credit constraints are, among others, provided by Banerjee and Newman (1993), Galor and Zeira (1993), Aghion and Bolton (1997), and Ottonello and Winberry (2024).

[2]The literature on the real effects of credit supply shocks is too large to be cited in full. A non-exhaustive list of representative examples includes Bernanke (1983), Chodorow-Reich (2014), Banerjee and Duflo (2014), Duygan-Bump, Levkov and Montoriol-Garriga (2015), and Huber (2018).

the view that credit constraints are widespread in the corporate sector. Distinguishing between these potential explanations for the overall low credit utilization observed in the data is critical for understanding if, and how, credit constraints affect firms and thereby the broader economy.

To this end, we introduce a simple dynamic model in which a firm's current financial decisions affect its financial condition in the future. The purpose of the model is not to propose a new theory of the financial decisions of firms, as it simply synthesizes elements from existing theories, but rather to help us delineate a dynamic concept of credit constraints and interpret what we observe in the data.

In the model, a firm decides how much to borrow subject to a collateral constraint that limits current borrowing to a fraction of its expected next-period cash flow. The firm is uncertain about its future productivity (and thereby its future cash flow) as well as the future tightness of the collateral constraint (the fraction of its cash flow that it can borrow). The uncertainty exposes the firm to the risk of becoming illiquid, which is costly due to credit-market frictions. The measure of dynamic credit constraints that emerges from the model is then captured by the expected marginal cost of borrowing, which is the sum of two components: (i) the current marginal cost (interest rate today) and (ii) the increase in the expected future cost of illiquidity induced by higher borrowing today. This measure of credit constraints captures not only how tight credit is in the current period, but also the expected cost of tight credit constraints in the future.

Since the expected cost of illiquidity increases with uncertainty, the firm optimally chooses to reduce borrowing when uncertainty increases. This property of the model emphasizes a potential fallacy in using static measures of credit constraints, such as measures that classify firms as more constrained when actual borrowing is closer to their current borrowing capacity. This is because a firm may choose to stay below its current capacity simply because more borrowing today increases the risk of binding constraints in the future. If so, the low utilization of credit indicates that the firm faces tighter dynamic credit constraints, not that it is unconstrained.

While it is straightforward to define a dynamic concept of credit constraints in the context of a theoretical model, it is difficult to measure it empirically. This is because we do not directly observe how current borrowing affects the expected marginal cost of future borrowing. In the data, we typically observe current prices and quantities, but not expectations of the future cost of illiquidity. However, we can construct these expectations indirectly using the quantitative predictions of the model.

The model delivers two main predictions. First, dynamically constrained firms decrease borrowing in response to increases in uncertainty about future access to credit. Second, the borrowing of a dynamically constrained firm responds to changes in the credit limit even if its borrowing constraint is slack prior to the limit change. Taking these predictions to the data enables us to assess whether tight dynamic constraints are likely to be an explanation for the low credit utilization observed in the data.

We begin by testing the prediction that higher productivity uncertainty—measured by the within-firm standard deviation of cash-flow-to-assets ratio—is associated with lower credit-line utilization rates. The results show that the difference in the average utilization rate between firms at the top and bottom of the cash-flow volatility distribution is 4.2 percent, corresponding to 19 percent of the mean utilization rate in the sample. Next, we assess the effects of financial uncertainty, proxied by the maturity of a firm's credit lines. The idea is that the quantity and price of credit are renegotiated when credit lines mature, implying firms are less certain about future access to credit as their credit lines approach maturity. We find that firms with long maturity have, on average, utilization rates 10.4 percentage points higher than firms with short maturity. This difference is substantial, considering the average utilization rate in the sample is 22.6 percent. The relationship between uncertainty and credit-line utilization rates observed in the data is consistent with the notion that many firms face tight dynamic credit constraints.

To test the second prediction of the model—that changes in credit limits affect current borrowing even if the firm is not constrained in the current period—we need measures of credit limit shocks that are exogenous to the firm's real performance. However, measuring these shocks directly from the data is challenging. Even if we use committed amounts on credit lines as proxies for credit limits, these changes are not independent of the firm's real performance and decisions. On the one hand, the committed amount could overstate a firm's borrowing capacity due to covenants that prevent the firm from fully utilizing its credit lines. On the other hand, the committed amount could understate the borrowing capacity if the firm chooses not to request credit line increases even when banks are willing to grant them. Moreover, changes in the committed amount could reflect changes in the firm's profitability, in which case the increase in borrowing is a consequence of higher investment opportunities rather than a pure increase in credit capacity.

Based on the above considerations, we do not use the measure of credit limit shocks derived from observed changes in committed amounts. Instead, we derive firm-level credit limit shocks indirectly through the structural estimation of the model. This approach allows us to infer a firm's borrowing capacity as the credit limit that rationalizes the actual borrowing observed in the data. The high correlation between the model-implied measure and the empirical measure based on committed amounts reassures us that the empirical measure serves as a good proxy for the actual credit limit.

The model-derived measure of firms' borrowing capacity fluctuates over time in response to two exogenous shocks: *productivity* and *financial* shocks. We can then use variations in borrowing capacity induced only by financial shocks (that are unrelated to productivity) to test the second prediction of the model, namely, that actual borrowing responds to credit-limit changes even if the limit is not binding prior to the shock. The estimation results show that firms increase borrowing, on average, by approximately 0.35 SEK for every SEK of limit increase. While the response is stronger for firms nearer their credit limit, it is statistically and economically significant also for firms that are far from the limit. We also find that financial shocks are the most important source of firm-level borrowing variation while productivity shocks play a minor role.

Related literature. Our study relates to several branches of literature. The first is the corporate-finance literature on firms' access to and use of credit lines. One of the contributions of our paper is to provide evidence with data that covers the near-universe of firms in Sweden, including the smallest firms. Most of the previous literature has relied on data covering only publicly listed or very large firms (see, e.g., Sufi, 2009, Acharya et al., 2020, and Chodorow-Reich and Falato, 2021). Two recent exceptions are Greenwald, Krainer and Paul (2020) and Chodorow-Reich et al. (2022), who use the Y-14 dataset from the Federal Reserve to study how firms' access to and use of credit lines vary over the size distribution.[3]

Chodorow-Reich et al. (2022) find that small firms are subject to more lender discretion than large firms and, therefore, may be unable to tap their credit lines in adverse states of the world. Credit-line borrowing is thus riskier for small firms, which is consistent with our finding that small firms normally draw less on credit lines than large firms. Greenwald, Krainer and Paul (2020) show that large firms often draw down their credit lines following adverse macroeconomic shocks and that this crowds out term lending to smaller firms. The key message is that the distributional aspect of credit-line drawdowns amplifies the decline in aggregate investment following adverse shocks.

Also related is the study by Aydin and Kim (2024), which employs experimental data on Turkish SMEs to examine how firms' borrowing responds to exogenous changes in credit limits. The study finds that firms increase borrowing in response to a credit line expansion, even when credit utilization was low prior to the increase. We conduct a similar test but we adopt a different approach to generate firm-level shocks: rather than assigning random credit limit increases to a random sample of firms, we construct the credit shocks indirectly with the structural estimation of the model.

The second branch of literature relevant to our study comprises theoretical research on credit constraints. As noted earlier, our goal is not to propose a new theory, but to synthesize mechanisms embedded in more complex models that helps us understand the main features of the data. The model also enables us to construct indirect measures of borrowing capacity through its structural estimation. In this respect, our paper is related to Nikolov, Schmid and Steri (2019) which estimates a dynamic firm financing model with frictions based on limited enforcement, moral hazard, and trade-off theory. Their objective is to assess which types of frictions are most relevant for the financial decisions of firms. We use a less detailed model that does not distinguish the sources of frictions because our aim is to assess the utilization of credit lines, not the origins of the credit limits.

[3] Other exceptions include Berger and Udell (1995) and Jiménez, Lopez and Saurina (2009), who use data from the Survey of Small Business Finance and the credit register of the Spanish central bank, respectively. Dinlersoz et al. (2018) is another study that analyzes the financial structure of both private and public firms, although the focus is not on credit lines.

The dynamic feature of credit constraints embedded in the model derives from uncertainty in future collateral constraints. This generates a risk of incurring future financial costs and thereby leads to precautionary behavior. A similar precautionary behavior is present in consumption and saving models where agents face uninsurable idiosyncratic risks (e.g., Leland, 1968, Bewley, 1977, Imrohoroğlu, 1989, Deaton, 1991, Huggett, 1993, Aiyagari, 1994, Carroll, 1997, and Guerrieri and Lorenzoni, 2017). It is also present in many corporate-finance models such as Riddick and Whited (2009) and Rampini and Viswanathan (2010).[4] Other papers highlighting the importance of the interaction between credit-market frictions and uncertainty include Christiano, Motto and Rostagno (2014), Gilchrist, Sim and Zakrajšek (2014), Arellano, Bai and Kehoe (2019), Favara, Gao and Giannetti (2021), and Alfaro, Bloom and Lin (2022).

One potential issue with our analysis is that firms use credit lines primarily for financing working capital, as in Banerjee and Duflo (2014). Consequently, the analysis may not be very informative about the financing of fixed investments.[5] That said, working capital is an important part of a firm's financial structure and features prominently in the recent literature on credit constraints, including studies that explore the employment effects of credit-supply shocks (e.g., Chodorow-Reich, 2014; Duygan-Bump, Levkov and Montoriol-Garriga, 2015; Bentolila, Jansen and Jiménez, 2018; and Benmelech, Bergman and Seru, 2021).

2 Data

The empirical analysis is based on two main data sets which we merge using a unique identifier (*organisationsnummer*) assigned to every Swedish firm. The first is the credit registry KRITA, collected and maintained by Statistics Sweden on behalf of Sveriges Riksbank, the central bank

[4] Gross and Souleles (2002) and Aydin (2022), among others, provide empirical evidence on the importance of the precautionary motive among households based on consumption responses to credit expansions. On the firm side, the precautionary motive has mainly been documented in the context of corporate cash holdings, for example, by Almeida, Campello and Weisbach (2004), Riddick and Whited (2009), and Acharya and Steffen (2020). We complement these papers by showing the importance of uncertainty and precautionary behavior for understanding the utilization of credit lines.

[5] To be clear, the mechanism embedded in our model applies equally well to term loans and fixed investments, but we do not provide direct evidence on whether firms have unused borrowing capacity for undertaking fixed investments.

of Sweden. KRITA is the Swedish component of ESCB's pan-European credit registry AnaCredit, which it follows closely in terms of data structure and variable definitions.

KRITA contains detailed monthly data on the universe of loans extended by around 20 Swedish monetary financial institutions to Swedish companies from 2019 and onwards. The reporting institutions account for 95 percent of the outstanding volume of bank loans to Swedish companies, which makes KRITA close to a census of corporate loans in Sweden.[6] For each loan reported in KRITA, we observe a broad set of information, such as outstanding amount, committed amount, loan type, maturity, as well as information about the borrowing firm, including its size, industry, location, legal form, and group affiliation.

The second data set is Serrano, which comprises annual financial-accounts data, as well as demographic and other firm-level information for the universe of Swedish corporate firms (*aktiebolag*). Serrano is provided by the Swedish credit bureau Bisnode and is based on the financial statements that Swedish corporate firms are required to submit to the Swedish Companies Registration Office every year in accordance with EU standards. Since Swedish firms are largely free to choose when their fiscal year starts and ends, many observations in the data are not correspond to calendar years. We deal with this issue by interpolating the financial statements so that each observation corresponds to a calendar year.[7] For each firm and year, we observe a wide range of balance-sheet and income-statement variables, as well as demographic variables such as registration date, industry, location, and group affiliation. We complement the firm-level data in Serrano with estimates of a firm's probability of default estimated by the Swedish credit bureau UC AB on the basis of a scoring model.

[6]The missing loans are mainly from very small banks, such as local savings banks—this is because KRITA's reporting requirement for monetary financial institutions is determined by ranking lenders in terms of size, from largest to smallest, and then moving down the list until the included lenders jointly account for 95 percent of the total volume of corporate loans. Since large firms rarely borrow from small banks, the loans that we fail to observe are predominantly loans to small firms. Hence, to the extent that missing loans bias our analysis, it is primarily by understating the prevalence and importance of credit lines among small firms.

[7]The length of the fiscal year is 12 months in the majority of cases, but it may occasionally be shorter or longer. This mainly happens when a firm enters or exits, or when it changes the timing of its fiscal year. Observations corresponding to fiscal periods longer or shorter than 12 months are straightforwardly handled by our interpolation approach. See Amberg et al. (2021) for a more detailed description of the interpolation procedure.

2.1 Sample composition

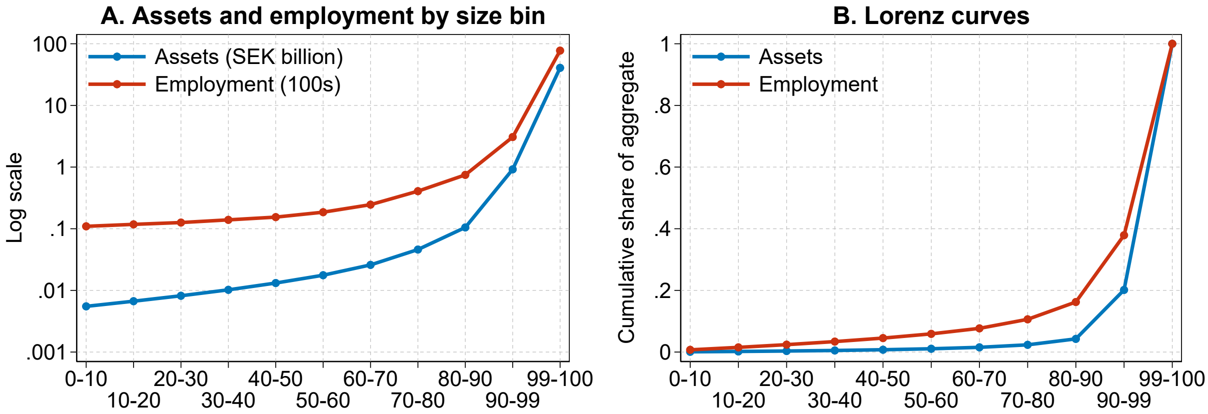
The main strength of our data is that it covers the universe of non-financial corporate firms, including small and micro-sized enterprises. We nevertheless impose a minimum size threshold to ensure that we only have active and economically meaningful enterprises in our sample. More specifically, we retain firms that have at least five employees as well as net assets and annual sales amounting to at least five million SEK (approximately 500,000 USD). Net assets is defined as assets minus cash holdings. We will henceforth refer to net assets simply as assets, and use the term total assets when referring to assets inclusive of cash. The resulting sample includes around 26,000 firms per time period.

Even with the lower size threshold there is substantial size dispersion in the sample: for example, average assets is around five million SEK in the bottom size decile, but over 41,000 million SEK (approximately 4.1 billion USD) in the top percentile. The size dispersion in the sample is illustrated in Figure 1, which plots average assets and employment for eleven size bins (Panel A), as well as their corresponding Lorenz curves (Panel B). The size bins correspond to deciles of the assets distribution, except for the top decile, which we split in two separate bins: 90th to 99th and above the 99th percentile. The Lorenz curves show the strong size concentration of the corporate sector: for example, firms in the top decile of the distribution account for over 60 percent of total employment and 80 percent of corporate assets.

2.2 Variable construction and definitions

Throughout the empirical analysis, we work with a firm-month panel data set, constructed by aggregating the loan-level data to the firm-month level. For variables measuring loan amounts, we aggregate by summing over all relevant loans held by a firm in a given month. When we construct ratios based on loan-amount variables, like the credit-line utilization rate, we do so on the basis of the summed firm-month values. For example, we measure a firm's utilization rate in a given month as the ratio of the drawn amount summed over all credit lines held by the firm to the committed amount summed over the same lines. For other variables, like interest rate and maturity, we compute the firm-month value as the weighted average of the variable across all

Figure 1: The size distribution of sample firms



This figure plots average assets and employment in eleven bins of the asset distribution (Panel A), as well as Lorenz curves of assets and employment over the same size bins (Panel B). Employment refers to the average number of full-time equivalent employees at a firm during a given year. Note that the vertical axis in Panel A is log-scaled.

relevant loans in a given month, with the committed amount on each loan as weight.[8]

The focus of the empirical analysis is on credit lines, which we define as loans satisfying the following three conditions: (i) the borrower is allowed to use funds up to a pre-agreed limit (the committed amount) without notifying the lender in advance; (ii) the remaining available credit (the undrawn amount) decreases and increases as the borrower draws and repays funds, respectively; (iii) the loan can be used multiple times. Two loan types in KRITA/AnaCredit satisfy these conditions: *overdrafts* and *revolving credit other than overdrafts and credit card debt.* In December 2022, revolving credit accounted for around two thirds of the aggregate committed credit-line volume to firms in our sample, and overdrafts for the remaining third.

[8]We treat firms belonging to the same corporate group (*koncern*) as one firm. This implies that we: (i) use the consolidated financial accounts of the top parent company in a group while discarding the individual accounts of the subsidiaries; and (ii) aggregate all loan variables to the level of the top parent. Hence, subsidiaries are subsumed into the groups to which they belong rather than being treated as individual firms. We exclude firms belonging to foreign groups, since we don't observe their entire financial structure.

3 Facts about firms' credit-line access and utilization

We present five stylized facts that emerge from the data described in the previous section.

Fact 1 *Credit lines are widespread and sizable, but not heavily used.*

More than half of all non-financial firms in Sweden have at least one credit line from a bank (Table 1, Panel A). Hence, a majority of non-financial firms in the economy are able to draw bank credit on demand and without notifying the bank in advance. The asset-weighted share of firms with a credit line is almost 90 percent, which implies that nearly all economic activity in the Swedish non-financial corporate sector is accounted for by firms with credit-line access. Conditional on a firm having at least one credit line, the committed amount on average equals 13 percent of the firm's net assets, or five times their monthly labor costs (Table 1, Panel B). Credit lines are thus not only common, but also provide firms with an economically significant amount of borrowing capacity.

However, the average utilization rate on credit lines—defined as the ratio of drawn to committed amount—is only 23 percent (Table 1, Panel B). The fact that committed amounts are large but utilization rates are low implies that firms have access to large amounts of unused borrowing capacity. More precisely, conditional on a firm having a credit line, the undrawn amount on average equals nine percent the value of firms' assets, or three times their monthly labor costs (Panel B). Thus, a large fraction of firms—namely, those with credit lines—could expand their operations by using more of the credit they have already been granted.

The importance of credit lines becomes even clearer in a comparison of different types of bank credit: 51 percent of Swedish non-financial firms hold a credit line, compared to 46 percent for term loans, 34 percent for financial leases, and 19 percent for all other loan types taken together (including non-revolving credit lines). As shown in Panel A of Figure 2, the predominance of credit lines holds throughout the size distribution. In terms of the aggregate committed amount of loans to non-financial firms, credit lines are second to term loans, accounting for 35 percent compared to 47 percent for term loans. The predominance of term loans holds over most of the size distribution, but not in the top percentile, where credit lines and term loans

Table 1: Firms' access to and utilization of credit lines

	Mean	25th pct.	Median	75th pct.	Number of observations	Number of firms
A. All firms						
Share with credit line	0.512	0.000	1.000	1.000	693,812	26,563
Share with credit line (weighted)	0.862	1.000	1.000	1.000	693,812	26,563
B. Firms with at least one credit line						
Committed amount/Net assets	0.134	0.048	0.094	0.174	355,456	14,253
Committed amount/Labor costs	4.534	1.095	2.301	4.762	336,784	13,628
Utilization rate	0.226	0.000	0.000	0.454	355,456	14,253
Undrawn amount/Net assets	0.093	0.029	0.064	0.123	355,456	14,253
Undrawn amount/Labor costs	2.853	0.727	1.544	3.197	336,784	13,628
Interest-rate spread	0.038	0.028	0.038	0.046	355,450	14,253

This table shows descriptive statistics for variables measuring firms' access to and utilization of credit lines. The sample spans the period December 2019 to December 2022 and comprises all non-financial firms in Sweden with at least five employees and five million SEK in sales and net assets. Net assets are total assets net of cash holdings and labor costs the average monthly labor cost during the year covered by the latest available financial statement. The interest-rate spread is the interest rate on the drawn amount minus the six-month T-bill rate.

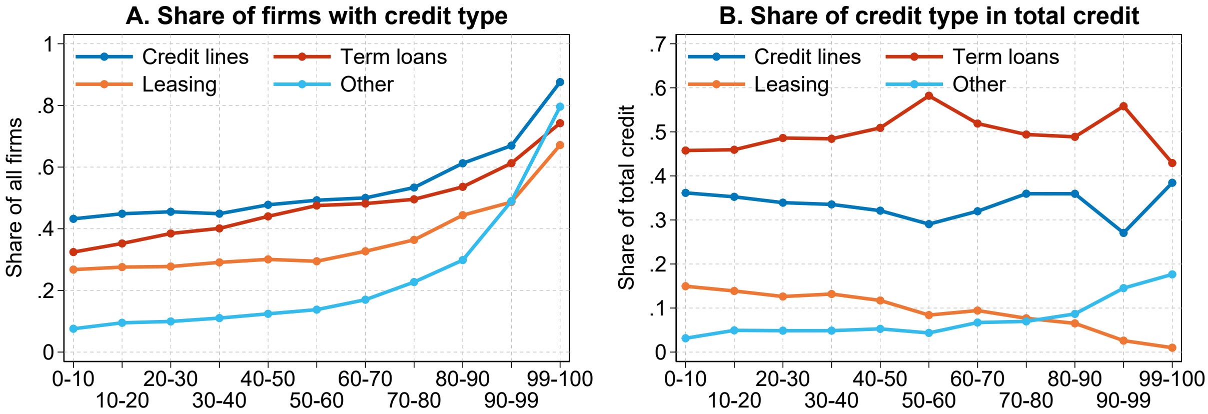
account for equal shares of total credit (Figure 2, Panel B).[9] Outside of the real-estate sector, however, credit lines are quantitatively the most important loan type, accounting for 42 percent of the aggregate committed loan volume, compared to 38 percent for term loans. Credit lines are thus a key source of external finance for non-financial firms.

Fact 2 *The marginal cost of borrowing from a credit line is not prohibitively high.*

The price of a credit line has two main parts: a fee for the maintenance of the facility as a whole and an interest rate charged on the drawn amount, i.e., the actual amount of borrowing at any given point in time (Berg, Saunders and Steffen, 2016). The overall maintenance fee is usually

[9]The increasing importance of other loan types in the top of the size distribution is due to non-revolving credit lines, which we treat as a loan type distinct from revolving credit lines (see the discussion in section 2.2 above).

Figure 2: Credit types over the size distribution



Panel A shows the share of firms in each size bin that has a given type of credit. Panel B shows the share of the total committed amount of credit in each size bin that is accounted for by each credit type. The category 'other' comprises non-revolving credit lines, factoring, and credit cards.

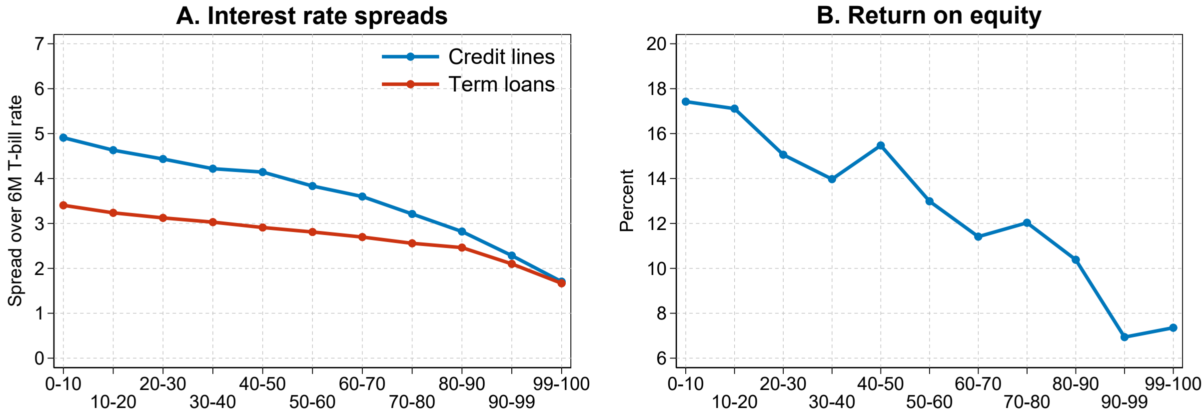
charged either as a percentage of the undrawn amount (*commitment fee*) or as a percentage of the committed amount (*facility fee*). The interest rate, in turn, is typically specified as a spread over some base rate and determines the marginal cost of borrowing from the line. In most cases, the interest rate on a credit line is not dependent on how much the firm draws, which implies that the marginal cost is flat up to the limit.[10]

The average interest spread on credit lines in our sample is 3.8 percent (Table 1, Panel B). The spread decreases monotonically over the size distribution, going from 4.9 percent in the bottom decile to 1.7 percent in the top percentile (Figure 3, Panel A).[11] These interest spreads—which are similar to those reported by Greenwald, Krainer and Paul (2020) and Chodorow-Reich et al.

[10]The exception is credit lines with *utilization fees*: in these cases, the interest paid on the entire drawn amount increases when the utilization rate exceeds a specified threshold (such as 30 or 50 percent), which creates a spike at the threshold in an otherwise flat marginal cost function. However, given the limited use of utilization fees—Berg, Saunders and Steffen (2016) document that no more than 11 percent of syndicated credit lines in the U.S. have utilization fees—most firms with credit lines face a flat marginal cost of borrowing up to the limit. The mean utilization fee in their sample is, moreover, relatively low at 12 basis points.

[11]Credit-line interest rates are only reliably reported for loan-month observations where the drawn amount is strictly larger than zero (the same is true in many other credit registers, such as the Federal Reserve's Y-14 data set). We therefore impute the credit-line interest rate for firm-month observations where the utilization rate is zero by assigning the average among observations in the same month-size bin-county-credit rating cell.

Figure 3: Interest rate spreads over the size distribution



Panel A plots the average interest rate on term loans (red line) and the drawn amounts on credit lines (blue line) within each bin of the asset distribution. Panel B plots the average return on equity in each size bin. The sample spans the period December 2019 to December 2022.

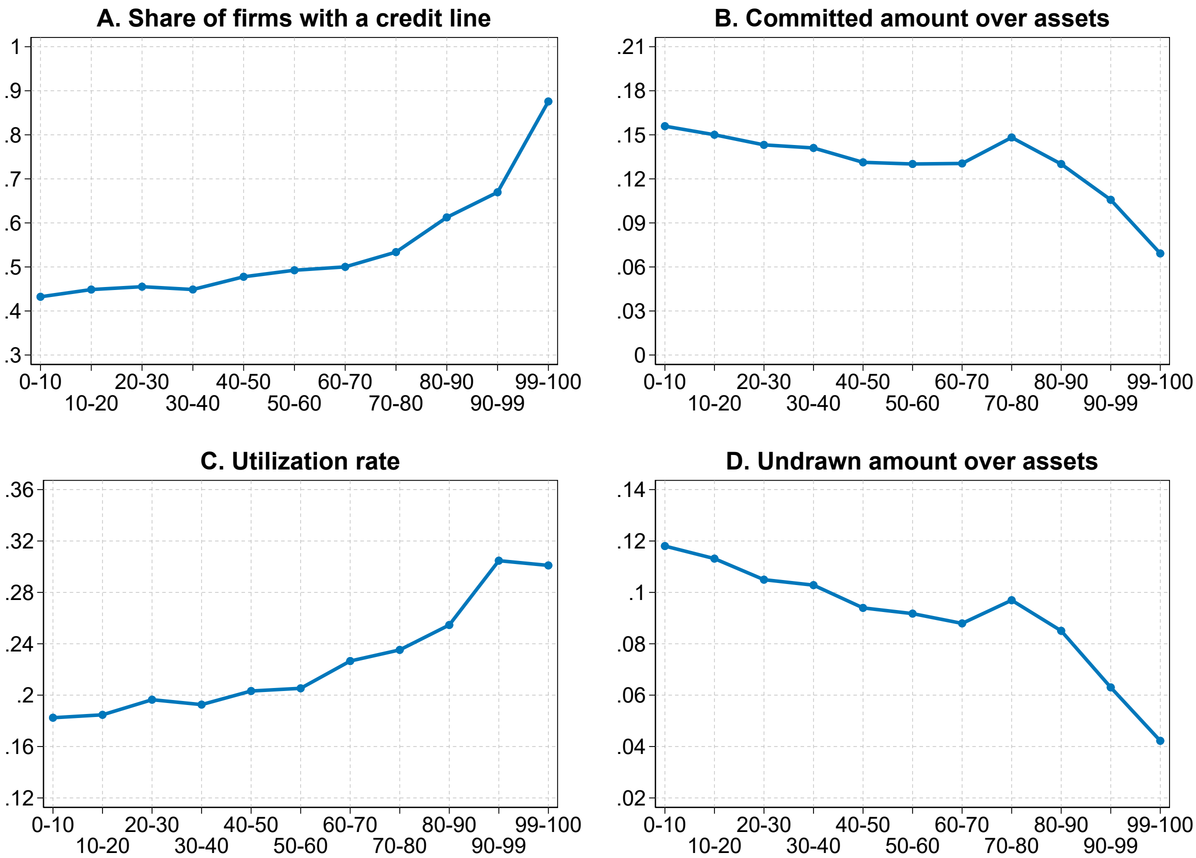
(2022) for the US in terms of level as well as size gradient—imply that firms that have credit lines face non-increasing and relatively low marginal costs of borrowing. The figure also shows that credit-line spreads on average are about one percentage point higher than term-loan spreads, but that the difference declines over the size distribution.

The second panel of Figure 3 shows the return on equity, which captures the cost of funding operations with equity. The average return on equity declines with firm size, going from about 17 percent for the smallest firms to around seven percent for the largest firms. Importantly, the cost of equity is substantially higher than the cost of debt throughout the size distribution, and especially so for smaller firms. This raises another question: if borrowing from credit lines is cheaper than equity, why do firms not replace equity financing with a higher usage of credit lines?

Fact 3 *Credit lines are more prevalent, but relatively smaller, in the top of the size distribution.*

Next, we consider how firms' access to and utilization of credit lines vary over the size distribution. To this end, we compute the mean of four credit-line characteristics within each bin of the size distribution: (i) an indicator for whether the firm has a credit line; (ii) the committed amount over net assets; (iii) the utilization rate; and (iv) the undrawn amount over net assets. The results are plotted in Figure 4.[12]

Figure 4: Firms' access to and utilization of credit lines over the size distribution



This figure plots the averages of various credit-line characteristics within each bin of the net-asset distribution. Panel A is based on all firms in the sample, whereas Panels B-D concern firms that have at least one credit line from a bank. The sample spans the period December 2019 to December 2022.

To begin with, the share of firms having at least one credit line from a bank is increasing over the size distribution, and particularly so in the upper part of the distribution: throughout the

[12]The facts reported in Figure 4 are robust to excluding the COVID-period from the sample, as shown in Figure B1 in Online Appendix B.

first eight deciles of the distribution, the share is fairly stable at around 50 percent, but it then increases markedly and reaches 88 percent in the top percentile (Panel A). This shows that firms throughout the size distribution have access to financing via credit lines, and particularly so in the top of the distribution.

The size of credit lines—measured by the ratio of committed amounts to net assets among firms that have a credit line—also varies over the size distribution, but in the opposite direction. The average ratio lies in the range 13–16 percent in the first eight deciles of the distribution and then declines sharply over the top two deciles, down to seven percent in the top percentile (Panel B). Credit-line size, measured relative to assets, is thus declining in firm size. The fact that the aggregate volume of committed amounts is heavily concentrated in large firms is thus not due to large firms having (relatively) larger credit lines, but reflects the strong concentration of the corporate sector.

Fact 4 *Credit-line utilization rates increase with firm size.*

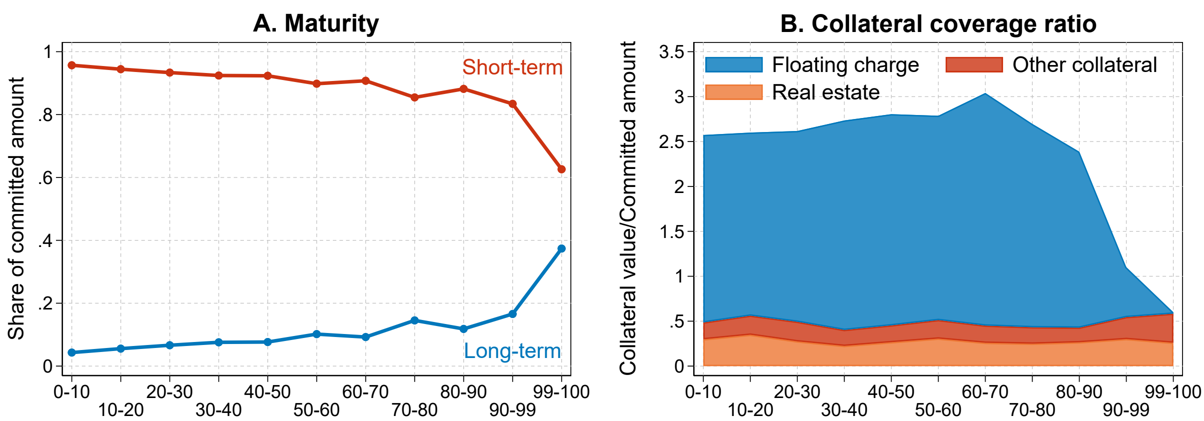
Panel C of Figure 4 shows that utilization rates on credit lines increase over the firm-size distribution, and especially in the upper part of the distribution: the average utilization rate is 18 percent at the bottom of the distribution, 21 percent in the middle, and 30 percent in the top. This demonstrates that the largest firms draw more on their credit lines than smaller firms. That the average size of credit lines (relative to firms' assets) is decreasing over the size distribution while the average utilization rate is increasing implies that undrawn amounts, as a percentage of assets, are decreasing in firm size. This can be seen in Panel D, which shows that the average ratio of undrawn amount to net assets goes from 12 percent in the bottom decile to four percent in the top percentile. Hence, conditional on having a credit line, small firms have access to more unused borrowing capacity via credit lines than large firms, when measured relative to assets.

The finding that utilization rates increase over the size distribution differs from the findings of Greenwald, Krainer and Paul (2020), who use the Federal Reserve's Y-14 data to document that the average utilization rate among U.S. firms hovers between 40 and 50 percent throughout most of the size distribution and then *declines* sharply in the top deciles. However, the difference in results mostly derives from differences in sample composition: when we impose the same sample restriction as in the Y-14 data—namely, only including loans with at least 10 million SEK in committed amount (roughly 1 million US dollars)—we find that the average utilization rate lies in the range 30-40 percent throughout most of the size distribution, and then declines sharply to just over 10 percent in the top of the distribution (see Figure B2 in Online Appendix B). The two analyses thus yield broadly consistent conclusions once we account for differences in sample composition.

Fact 5 *Large firms post less collateral and have credit lines with longer maturities.*

Our final stylized fact concerns the maturity and collateral coverage of credit lines, and how they vary over the size distribution. The majority of credit lines—about 70 percent of the aggregate committed amount—have short maturities at origination (one year or less). The share of short-maturity lines is particularly high among small firms: the share of long-maturity credit lines exceeds 20 percent only in the top decile of the size distribution; among smaller firms, virtually all credit lines have short maturities (Figure 5, Panel A).

Figure 5: Credit-line characteristics over the size distribution



Panel A shows the share of long-term and short-term credit lines—defined as lines with initial maturities above and below one year, respectively—in each size bin. Panel B displays the collateral coverage ratio of credit lines—defined as the ratio of the current value of collateral backing credit lines to the committed amount in each size bin—as well as a breakdown by type of collateral.

Credit lines are typically heavily collateralized: the collateral coverage ratio—defined as the ratio of the current value of collateral backing credit lines to the committed amount—is around 2.5 throughout most of the size distribution. In the top of the distribution, however, the collateral coverage ratio is substantially lower: 1.1 among firms between the 90th and the 99th percentiles, and 0.6 in the top percentile (Figure 5, Panel B). Hence, the requirement to post collateral when obtaining a credit line is substantially lower for large firms than for small firms. The predominant type of collateral backing credit lines is the 'floating charge', which accounts for around 80 percent of the collateral value in the first nine deciles of the size distribution.[13] In the top of the size distribution, on the other hand, credit lines are rarely secured by floating charges. Instead, credit lines to large firms tend to be either unsecured or backed by some other type of collateral, such as real estate or other fixed assets.

3.1 Robustness and alternative specifications

Measuring utilization rates over time. Firms' funding needs often vary over time due to seasonal factors. One may therefore argue that the relevant measure for determining whether a firm is credit constrained is not the average but the maximum utilization rate over longer periods of time. Suppose, for example, that a firm has a credit line as its only source of external finance. Furthermore, suppose that the firm exhausts the credit line one month per quarter due to predictable seasonal variation in demand, but does not need to use it at all during the other two months. One can plausibly argue that such a firm faces a binding borrowing constraint even though its average utilization rate over time is only one third, because it frequently and predictably hits its borrowing limit.

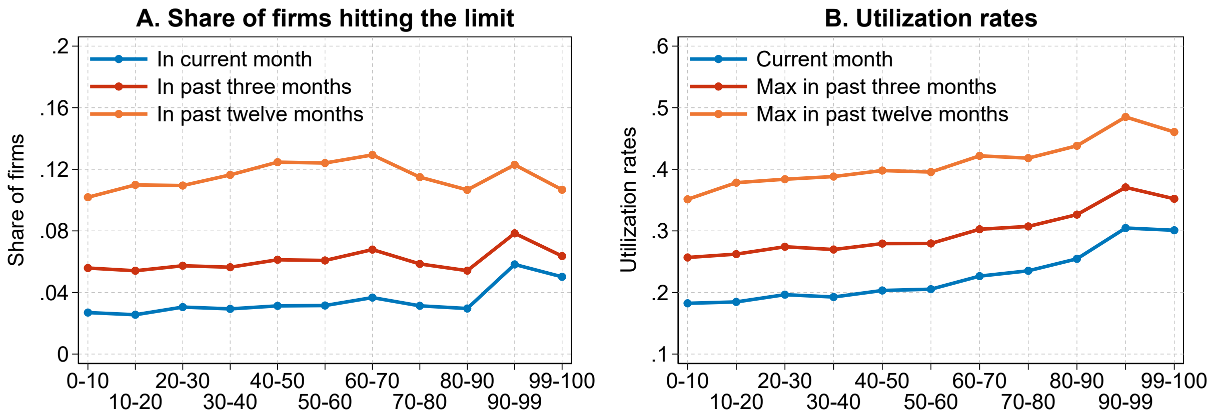
Figure 6 shows, however, that the overall message does not change fundamentally when we consider measures of firms' maximum utilization rates over longer periods of time. Panel A plots the shares of firms that have exhausted their credit lines in a given month, as well as at any point during the past three and twelve months, respectively.[14] The share of firms hitting the

[13] A floating charge (also known as a floating lien) is a security interest in a pool of non-constant assets—i.e., a pool of assets that may change in quantity and value over the lifetime of a loan—the majority of which typically consists of accounts receivable and inventories.

[14] We classify a firm as having exhausted its credit lines if the sum of the used amounts over all credit lines exceeded 95 percent of the sum of the committed amounts.

limit is low for all time spans. For example, only 12 percent of firms ever hit the limit during a given twelve-month period. A similar picture emerges in Panel B, where we plot the average maximum utilization rate in each size bin for the same time spans. The average maximum over a year is 41 percent in the sample as a whole, which implies that most firms are never close to exhausting their available credit. Notice that the share of firms hitting the limit, as well as the average maximum utilization rate, increases over the size distribution, which corroborates the conclusion that small firms use their credit lines less than large firms.

Figure 6: Measuring firms' maximum utilization rates over time



Panel A plots the share of firms in each size bin that exhaust their credit lines in a given month (blue line) as well as at any point in the past three and twelve months (green and red lines, respectively). We define a firm as having exhausted its credit lines if it has drawn more than 95 percent of the committed amounts summed over all of its credit lines. Panel B shows the average utilization rate (blue line) as well as the average maximum utilization rate over the past three and twelve months (green and red lines, respectively) in each size bin.

Covenant-adjusted measures. A relatively common feature of credit-line contracts are covenants, which specify conditions that the borrower has to satisfy in order to avoid having the loan renegotiated or revoked prior to its maturity date. Covenants may prevent some borrowers from using their credit lines in full, because doing so would lead them to violate some of the covenants. In such cases, the committed amount on a credit line overstates the actual borrowing capacity available to the firm.

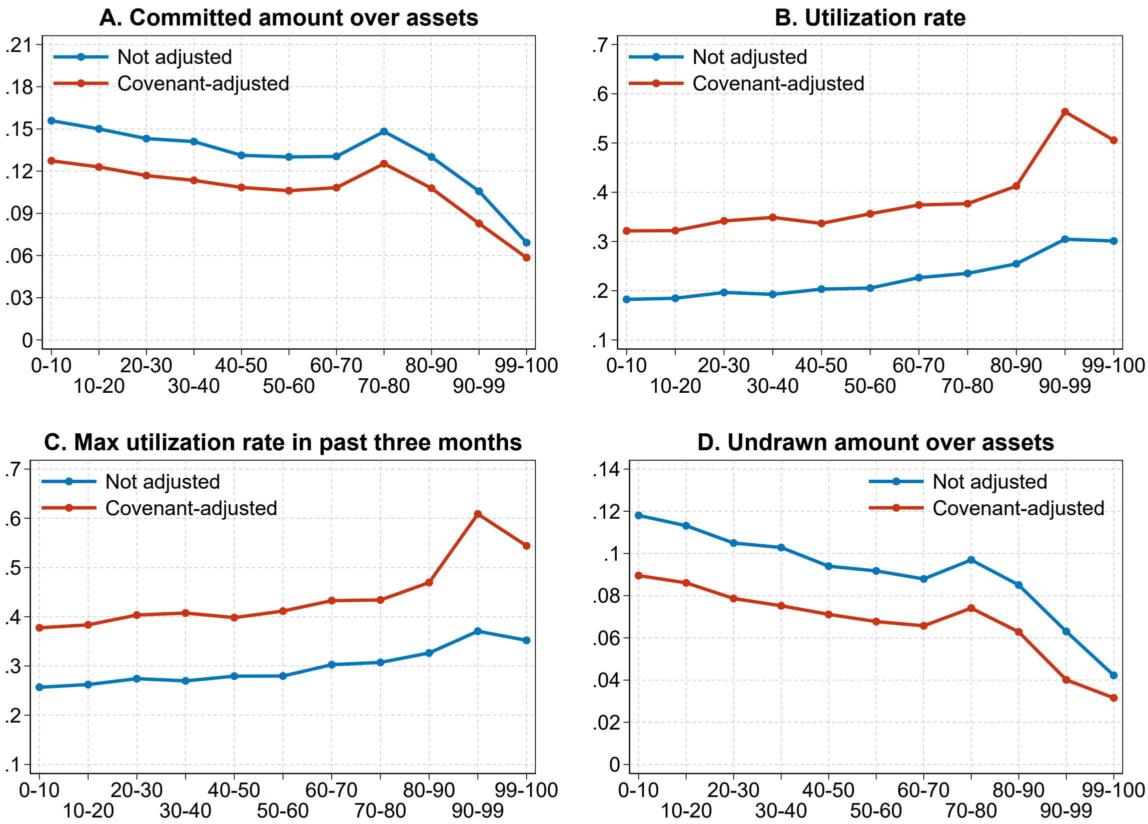
To get a better sense of the actual amount of unused borrowing capacity, we therefore recompute our main measures of the size and utilization of credit lines after covenant-adjusting the committed amounts—i.e., decreasing each firm's committed amount until the undrawn amount equals the increase in borrowing that the firm could undertake without breaking any covenant. We do not observe covenants in the data and therefore follow Greenwald, Krainer and Paul's (2020) approach for approximating covenant-adjusted committed amounts. This involves assuming that (i) all firms are subject to two of the most common covenants in debt contracts—a minimum interest coverage ratio and a maximum debt-to-earnings ratio—and (ii) the requirements on these ratios equal the average requirements in the sample of debt contracts studied by Greenwald (2019).[15]

While many credit line contracts do not contain explicit covenants—in particular among SMEs, where short maturities and high collateral requirements essentially function as substitutes for covenants—it is likely that banks impose informal restrictions on borrowers, and that these restrictions are similar to those imposed explicitly in contracts with covenants. Hence, our covenant-adjusted measures are likely informative about firms' true borrowing capacity even when the credit lines do not contain explicit covenants.

The covenant-adjusted measures of size and utilization of credit lines are reported in Figure 7 along with the non-adjusted measures. The covenant-adjustment has a noticeable impact on the measures of borrowing capacity and utilization, but not large enough to overturn our conclusions. More specifically, the average ratio of committed amount to net assets falls from 13 to 11 percent; the average utilization rate increases from 23 to 39 percent; the average maximum utilization rate in the past three months increases from 30 to 44 percent; while the ratio of undrawn amount to net assets declines from 9 to 7 percent. The respective size gradients, meanwhile, are hardly altered, with the exception that utilization rates in the top of the size distribution are more affected by the adjustment. Hence, the finding that firms throughout the size distribution have access to substantial amounts of unused borrowing capacity via credit lines is robust to the covenant-adjustment of the committed amounts.

[15] See online Appendix A for details on the construction of the covenant-adjusted measures.

Figure 7: Covenant-adjusted credit-line characteristics across the firm-size distribution



This figure plots the averages of various credit-line characteristics within bins of the firm-size distribution. We plot both the non-adjusted (blue line) and the covenant-adjusted (red line) measures. We describe the covenant-adjustment approach in general terms in Section 3.1 and in more detail in Online Appendix A.

4 A dynamic model of credit constraints

This section presents a model of firms' borrowing and hiring decisions from which we derive predictions that will be tested empirically (Section 5) and from which we construct firm-level measures of borrowing capacity by structurally estimating the model (Section 6).

Consider a firm with the production technology $Y_t = z_t N_t$, where N_t is employment and z_t is an idiosyncratic productivity shock that follows the first-order Markov process

$$z_{t+1} = \rho^z z_t + \epsilon_t.$$

The residual ϵ_t is log-normally distributed with parameters μ^z and σ^z.

Hiring is costly. A firm with current employment N_t and new employment N_{t+1} incurs the cost $\Upsilon\left(N_{t+1}/N_t\right)N_t$, where the function $\Upsilon(.)$ is strictly increasing and convex. This cost insures that the optimal size of an individual firm is determined at each point in time.

Although we specify the production input to be employment, we can relabel N_t to be capital and the model would have the same properties. In this case the function $\Upsilon(.)$ would represent capital adjustment costs.

The firm starts period t with debt B_t issued in the previous period $t-1$. After the realization of revenues, the firm issues new debt B_{t+1} at price q_t, the inverse of the gross interest rate. The new debt, however, is subject to the collateral constraint

$$B_{t+1} \leq \bar{\xi}_{t+1}\bar{z}_{t+1}N_{t+1}, \tag{1}$$

where $\bar{z}_{t+1} = \mathbb{E}_t z_{t+1}$ is the expectation of next period productivity and $\bar{\xi}_{t+1} = \mathbb{E}_t\xi_{t+1}$ is the expectation of a stochastic variable that affects the financial tightness of the firm.

The constraint links the borrowing capacity of the firm to the expected cash flow in the next period, $\bar{z}_{t+1}N_{t+1}$. Effectively, the cash flow acts as a collateral. However, only a fraction $\bar{\xi}_{t+1}$ of the expected cash flow can be used to enforce the debt. The dependence of the borrowing constraint is consistent with Lian and Ma (2021) showing that in the US 80% of debt is based predominantly on cash flows from firms' operations (cash flow–based lending). See also Greenwald (2016) for the significance of these constraints for mortgage borrowing.

We think of the borrowing limit $\bar{\xi}_{t+1}\bar{z}_{t+1}N_{t+1}$ as capturing the total committed credit that the firm receives from banks. This includes term borrowing as well as the committed amount of credit lines. The debt B_t, instead, captures the actual borrowing. Thus, the difference between the borrowing limit and the actual borrowing, $\bar{\xi}_{t+1}\bar{z}_{t+1}N_{t+1} - B_{t+1}$, is 'unused' credit. This is the model counterpart of the empirical measure of unused credit lines in the data.

The financial variable ξ_t also follows an independent first order Markov process,

$$\xi_{t+1} \quad = \quad \rho^{\xi}\xi_t + \varepsilon_t,$$

where the residual ε_t is log-normally distributed with parameters μ^{ξ} and σ^{ξ}. The stochasticity of ε_t plays an important role in the model and could reflect several factors. It could derive from shocks that affect the lending capacity of banks or from the reassessment of the firm's growth potential. Uncertainty could be especially high when the contractual agreements with banks approach renewal. A drop in ξ_t could also reflect, in reduced form, the failure to fully renew a term loan that has reached maturity or, as we will argue below, the arrival of a new investment opportunity.

The budget constraint of the firm is

$$B_t + D_t + \Upsilon\left(\frac{N_{t+1}}{N_t}\right)N_t = z_tN_t - w_tN_t + q_tB_{t+1}, \tag{2}$$

where D_t is the equity payout (dividends) and w_t is the wage rate. All other variables were defined earlier.

4.1 Firm's policies

The problem of the firm can be written recursively as

$$V_t(B_t, N_t) \quad = \quad \max_{B_{t+1},N_{t+1}} \left\{ D_t + \beta\,\mathbb{E}_tV_{t+1}(B_{t+1}, N_{t+1}) \right\}$$

subject to (1) and (2).

The function $V_t(B_t, N_t)$ is the equity value which depends on two endogenous states, debt B_t and employment N_t, in addition to the exogenous states z_t and ξ_t. To simplify the notation, the dependence on exogenous states is indicated by the time subscript t.

We now take advantage of the linearity of the model and normalize the problem by N_t so that all variables are expressed in per unit of employment. The normalized problem reads

$$v_t(b_t) \quad = \quad \max_{b_{t+1}, g_{t+1}} \left\{ d_t + \beta g_{t+1} \mathbb{E}_t v_{t+1}(b_{t+1}) \right\} \tag{3}$$

subject to:

$$d_t = z_t - w_t - \Upsilon(g_{t+1}) + q_t g_{t+1} b_{t+1} - b_t$$
$$\bar{\xi}_{t+1} \bar{z}_{t+1} \geq b_{t+1}.$$

The function $v_t(b_t) = V_t(B_t, N_t)/N_t$ is the value of the firm per employee, $d_t = D_t/N_t$ is the dividend paid to shareholders per employee, $b_t = B_t/N_t$ is the liabilities per-employee, and $g_{t+1} = N_{t+1}/N_t$ is the gross growth rate of total employment.

To characterize the policies of the firm, we derive the first order conditions with respect to b_{t+1} and g_{t+1}. Given $\lambda_t g_{t+1}$ the Lagrange multiplier for the enforcement constraint, the first order conditions are

$$q_t + \beta \mathbb{E}_t \frac{\partial v_{t+1}(b_{t+1})}{\partial b_{t+1}} = \lambda_t,$$
$$q_t b_{t+1} + \beta \mathbb{E}_t v_{t+1}(b_{t+1}) = \Upsilon'(g_{t+1}).$$

The envelope condition provides the derivative of the firm value, which is equal to $\partial v_t(b_t)/\partial b_t = -1$. This shows that the normalized value of the firm is linear in normalized debt, b_t. The linear property allows us to rewrite the value of the firm as

$$v_t(b_t) = \hat{v}_t - b_t, \tag{4}$$

where $\hat{v}_t$ depends only on the exogenous states (shocks). The first order conditions can then be rewritten as

$$q_t = \beta + \lambda_t, \tag{5}$$

$$(q_t - \beta)b_{t+1} + \beta \mathbb{E}_t \hat{v}_{t+1} = \Upsilon'(g_{t+1}). \tag{6}$$

Condition (5) determines the optimal choice of debt. The left-hand-side is the marginal benefit of borrowing: by increasing b_{t+1} by one unit, the firm increases the dividend by q_t. The first term on the right-hand-side is the marginal cost of borrowing: if the firm increases b_{t+1} by one unit, it must repay that unit in the next period. However, since the repayment is in the next period, the present value is β. If $q_t > \beta$, the marginal benefit is always bigger than the cost. Therefore, the firm borrows as much as possible until it reaches the limit. This implies that the borrowing constraint is binding and, therefore, the multiplier λ_t is positive.

Condition (6) determines the optimal employment growth, g_{t+1}. The left-hand-side is the marginal benefit resulting from the sum of two terms. The first term captures the fact that higher employment allows the firm to increase its debt by b_{t+1}. This is because employment acts as a collateral through higher cash flows. The net benefit is $(q_t - \beta)b_{t+1}$. The second term captures the fact that higher employment increases the value of the firm by $\beta \mathbb{E}_t \hat{v}_{t+1}$. Remember that $\hat{v}_{t+1}$ is the value of one employee. The right-hand-side is the marginal cost of employment growth, which is captured by the derivative of the adjustment cost, $\Upsilon'(g_{t+1})$.

The following proposition characterizes the firm's policy.

Proposition 4.1 *If $q_t > \beta$, the borrowing constraint binds and the growth of employment increases in $\bar{\xi}_{t+1}$ and $\bar{z}_{t+1}$. If $q_t = \beta$, the debt is indeterminate and employment growth increases only in $\bar{z}_{t+1}$.*

Proof 1 *The borrowing constraint is binding if the multiplier λ_t is positive. Condition (5) shows that this is the case only if $q_t > \beta$. Since $\Upsilon'(g_{t+1})$ is increasing in g_{t+1} due to the convexity of the adjustment cost, condition (6) shows that $\Upsilon'(g_{t+1})$ must increase in b_{t+1} and $\mathbb{E}_t \hat{v}_{t+1}$. The latter depends positively on $\bar{z}_{t+1}$. Since an increase in $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ increases the debt, g_{t+1} must also increase. However, if $q_t = \beta$, b_{t+1} no longer enters condition (6). The growth of employment, then,* *depends only on $\mathbb{E}_t\hat{v}_{t+1}$, which is only a function of $\bar{z}_{t+1}$.* ■

The model described so far has two frictions: the adjustment cost in hiring and the borrowing limit. The proposition establishes that, if the debt is cheaper than equity, that is, $q_t > \beta$, the firm always borrows up to the limit. This implies that the firm always utilizes the whole borrowing capacity. The fact that hiring is risky or the borrowing limit is stochastic are irrelevant for the choice of credit utilization. In order to have partial utilization of the borrowing capacity we need to introduce an additional friction.

4.2 Financial distress

We introduce a second source of financial frictions by assuming that higher debt increases the likelihood of costly financial distress. With this additional friction, the borrowing constraint could be occasionally binding. We can then interpret the difference between the borrowing limit and actual borrowing as 'unused' lines of credit.

The firm enters the period with debt per-employee b_t chosen in the previous period. Given the realization of ξ_t and z_t at time t, the enforcement constraint might no longer be satisfied at this point, that is, $b_t > \xi_t z_t$. In this case the firm needs to raise $b_t - \xi_t z_t$ with alternative sources of funds that are costly. In particular, we assume that the cost incurred to access the alternative funds is $\kappa(b_t - \xi_t z_t)^\eta$. This is a 'financial distress cost' because it is paid to raise additional funds, which could also include, in the extreme, the cost of bankruptcy. However, we would like to interpret this cost more broadly. It could also reflect the stochastic arrival of investment opportunities. Entering the period with high debt limits the ability to raise more standard debt needed to fund the new investment and, as a result, forces the firm to raise alternative funds using more costly sources. If we interpret the borrowing capacity $\xi_t z_t$ as net of the funds absorbed by the new investment, the arrival of the investment opportunity will be captured in reduced form by a lower realization of ξ_t. Failure to fully renew a term loan will also be captured, in reduced form, by a lower realization of ξ_t.

The distress cost can be expressed more generally as

$$\varphi_t(b_t) = \kappa \cdot \left(\max \left\{ b_t - \xi_t z_t \ , \ 0 \right\} \right)^{\eta}, \tag{7}$$

where $\eta > 1$ so that the cost function is convex in b_t. The normalized problem solved by the firm becomes

$$v_t(b_t) \quad = \quad \max_{b_{t+1}, g_{t+1}} \left\{ d_t + \beta g_{t+1} \mathbb{E}_t v_{t+1}(b_{t+1}) \right\} \tag{8}$$

subject to:

$$d_t = z_t - w_t - \Upsilon(g_{t+1}) + q_t g_{t+1} b_{t+1} - b_t - \varphi_t(b_t)$$

$$\bar{\xi}_{t+1} \bar{z}_{t+1} \geq b_{t+1}.$$

The new problem is similar to the previous problem (3). The only difference is that the budget constraint also includes the cost $\varphi_t(b_t)$. Notice that the value function $v_t(b_t)$ is net of this cost. If $\varphi_t(b_t) = 0$ for all b_t, we go back to the previous specification of the model.

Although the addition of the convex cost may seem a minor modification, it has important implications for the optimal decisions of firms. As we will see, it generates a precautionary motive in the choice of b_{t+1} and leads to nonbinding borrowing constraints.

To characterize the optimal policies chosen by the firm, we derive the first order conditions from problem (8). Differentiating with respect to b_{t+1} and g_{t+1}, respectively, we obtain

$$q_t + \beta \mathbb{E}_t \frac{\partial v_{t+1}(b_{t+1})}{\partial b_{t+1}} = \lambda_t,$$

$$q_t b_{t+1} + \beta \mathbb{E}_t v_{t+1}(b_{t+1}) = \Upsilon'(g_{t+1}), .$$

The envelope condition returns $\partial v_t(b_t)/\partial b_t = -1 - \varphi_t'(b_t)$, which allows us to write the value function, net of the distress cost, as

$$v_t(b_t) = \hat{v}_t - b_t - \varphi_t(b_t). \tag{9}$$

The value of the firm is no longer linear in b_t but it is now concave: since $\varphi_t(.)$ is convex, its negative is concave. This generates a precautionary motive in the choice of debt.

Using the envelope condition, we can rewrite the optimality conditions as

$$q_t = \beta\Big[1 + \mathbb{E}_t\varphi'_{t+1}(b_{t+1})\Big] + \lambda_t, \tag{10}$$

$$(q_t - \beta)b_{t+1} + \beta\mathbb{E}_t\Big[\hat{v}_{t+1} - \varphi_{t+1}(b_{t+1})\Big] = \Upsilon'(g_{t+1}). \tag{11}$$

Condition (10) determines the optimal choice of debt. The left-hand-side is the marginal benefit of borrowing: by increasing b_{t+1} by one unit, the firm is able to increase current dividends by q_t. The first term on the right-hand-side is the marginal cost of borrowing: if the firm increases b_{t+1} by one unit, in the next period it has to pay back that unit. In addition—and this is what differentiates this problem from the previous problem—higher borrowing may increase the expected distress cost faced by the firm in the next period. The expected increase in distress cost is $\mathbb{E}_t\varphi'_{t+1}(b_{t+1})$. If the optimal debt is constrained, however, the marginal benefit is higher than the marginal cost: the firm would like to borrow more but the constraint does not allow it. The difference between the marginal benefit and the marginal cost of borrowing is captured by the multiplier λ_t.

Condition (11) determines the optimal employment growth, g_{t+1}. The left-hand-side is the marginal benefit resulting from the sum of two terms. The first term derives from the fact that higher employment allows the firm to increase its debt by b_{t+1}, which has a net benefit of $(q_t - \beta)b_{t+1}$. The second term captures the fact that higher employment increases the value of the firm, net of the distress cost, which is equal to $\beta\mathbb{E}_t[\hat{v}_{t+1} - \varphi_{t+1}(b_{t+1})]$. The right-hand-side is the marginal cost of employment growth, captured by the derivative of the adjustment cost, that is, $\Upsilon'(g_{t+1})$.

As in the model without financial distress, the variable $\hat{v}_t$ depends only on the exogenous shocks. The value function, however, is no longer linear in b_t. The convexity of the distress cost makes the surplus function concave, introducing a precautionary motive that discourages borrowing. Because of this, the firm may choose not to borrow up to the limit and the borrowing constraint could be occasionally binding.

Proposition 4.2 *If $q_t > \beta$ and κ is sufficiently large, the borrowing constraint is not binding. The growth of employment increases in $\bar{\xi}_{t+1}$ and $\bar{z}_{t+1}$, independently of whether the borrowing constraint is binding or not. If $q_t = \beta$ the debt is indeterminate and the growth of the firm depends only on $\bar{z}_{t+1}$.*

Proof 2 *See online Appendix A.*

Non-binding borrowing constraints capture limited credit utilization or unused lines of credit. We interpret the difference between the credit limit and the actual borrowing as unused credit, that is,

$$\text{Unused Credit} = b_{t+1} - \bar{\xi}_{t+1}\bar{z}_{t+1}.$$

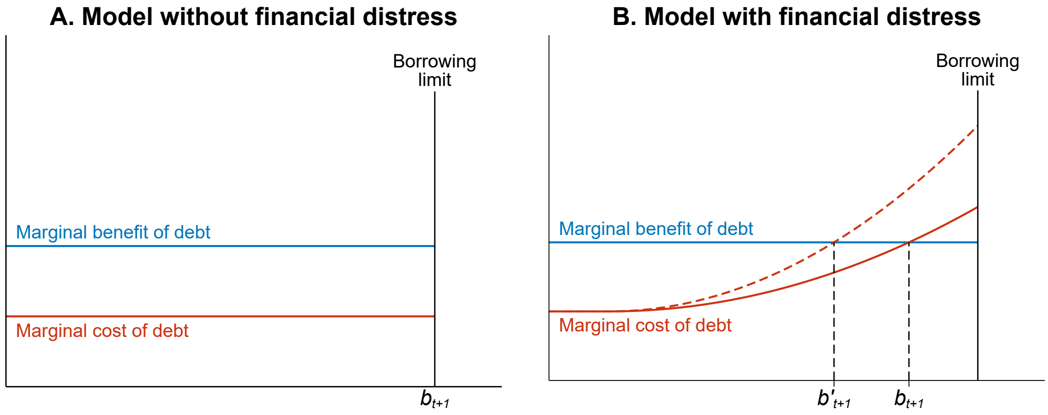
Another important point stated in the proposition is that, even if the borrowing constraint is not binding, higher borrowing capacity could have a positive impact on employment. The next proposition establishes the importance of uncertainty or risk. Let's first introduce some preliminary definitions.

Define $x = \xi z$ the product of the two shocks, ξ and z. The cumulative distribution function is denoted by $\Gamma(x)$. Now consider two distributions with the same mean $\bar{x}$ but different cumulative functions $\Gamma_A(x)$ and $\Gamma_B(x)$. Suppose that $\Gamma_A(x) < \Gamma_B(x)$ for all $x < \bar{x}$. What this implies is that, even if the two distributions have the same mean $\bar{x}$, values below the mean are less likely with A than with B. Since in our model financial distress arises for values below the mean, distribution B implies more risk for the firm. If the distributions are log-normal, the condition is satisfied if A has a lower standard deviation than B (but the same mean).

Proposition 4.3 *If $q_t > \beta$ and κ is sufficiently large, credit utilization and employment growth both decline when the distribution of $x_{t+1} = \xi_{t+1}z_{t+1}$ changes from Γ_A to Γ_B. If $q_t = \beta$, credit utilization and employment are not affected by the change in distribution.*

Proof 3 *We have shown in the previous proposition that, if $q_t > \beta$ and κ is sufficiently large, the borrowing limit is not binding. Equations (20) and (21) in the proof of Proposition 4.2 (see online Appendix A) imply that a change in the distribution of x_{t+1} from Γ_A to Γ_B increases $\mathbb{E}_t\varphi_{t+1}(b_{t+1})$*

Figure 8: Optimal debt policy



and $\mathbb{E}_t\varphi'_{t+1}(b_{t+1})$*. This is because lower values of* x_{t+1}*, which are associated with higher distress costs, are more likely when the cumulative distribution is* Γ_B*. Condition (10) then implies that* b_{t+1} *falls (lower credit utilization) and condition (11) implies that* g_{t+1} *declines (lower employment growth).* ■

The change in the distribution captures higher uncertainty or risk. Therefore, the model predicts that uncertainty—both productivity and financial—affects the utilization of credit. Even if the credit constraint is slack, higher uncertainty induces the firm to utilize less credit and to choose lower employment growth.

Figure 8 provides a graphical illustration of the optimal borrowing chosen by the firm. It plots the marginal benefit and cost of debt. The marginal benefit of borrowing is captured by the left-hand-side of condition (10): by increasing b_{t+1} by one unit, the firm increases dividends (consumption) by q_t. The marginal cost of borrowing is the first term on the right-hand-side: if the firm increases b_{t+1} by one unit, in the next period it has to pay back that unit, plus the increase in distress cost induced by higher borrowing. In the proof of Proposition 4.2 we have shown that $\varphi'_{t+1}(b_{t+1})$ increases in b_{t+1}. Thus, the expected marginal cost $\mathbb{E}_t[1 + \varphi'_{t+1}(b_{t+1})]$ increases in b_{t+1}.

The first panel depicts the model without financial distress. In this case, if $q_t > \beta$, the marginal benefit of borrowing is always bigger than the marginal cost and the firm always borrows up to the limit. The borrowing limit is indicated in the graph by the vertical line. The case with financial distress is depicted in the second panel. In this case the marginal cost (continuous line) is initially below the marginal benefit. However, as the debt increases, the expected cost of financial distress rises, inducing an increase in the marginal cost of borrowing. As a result, the firm does not borrow up to the limit (if κ is sufficiently large).

The dashed line in the second panel captures two changes. The first is an increase in the distress cost generated by an increase in the parameter κ: the higher is the value of κ, the larger is the difference between the borrowing limit and the actual debt chosen by the firm. The second captures an increase in the volatility or dispersion of the idiosyncratic shocks z_{t+1} and ξ_{t+1}: higher volatility increases the expected marginal cost associated with financial distress, for any level of debt. This is captured in the graph by the upward shift in the marginal cost of debt (dashed line). As a result, the optimal debt chosen by the firm becomes smaller (lower utilization of credit).

5 Uncertainty and credit-line utilization in the data

In this section, we test the prediction that an increase in uncertainty about future productivity or future access to credit leads firms to reduce credit-line utilization today (Proposition 4.3). We consider productivity uncertainty first and then financial uncertainty.

5.1 Productivity uncertainty

Productivity uncertainty is captured in the model by the dispersion of productivity: the larger is the dispersion of next period z, the higher is the expected cost of financial distress for any given level of debt chosen today. A higher dispersion of z thus induces the firm to borrow less today (Proposition 4.3).

Following Bates, Kahle and Stulz (2009) and Favara, Gao and Giannetti (2021), we proxy for productivity uncertainty with the median cash-flow volatility in the two-digit industry in which a firm operates. This measure is constructed in two steps. First, we compute the standard deviation of the ratio of EBITDA to total assets over the preceding ten years for each firm i and year t. We then compute the industry-level cash-flow volatility as the median cash-flow volatility across all firms in industry j in year t.

To test whether higher productivity uncertainty is associated with lower utilization rates, we estimate the following regression equation:

$$Y_{i,t} = \alpha_{s,r,t} + \beta \cdot \sigma_{j,t}^{EBITDA} + \gamma \cdot X_{i,t} + \varepsilon_{i,t}. \tag{12}$$

The dependent variable, $Y_{i,t}$, is a measure of firm i's credit-line utilization rate at the end of year t. $\sigma_{j,t}^{EBITDA}$ is the median cash-flow volatility in firm i's industry in year t and $\alpha_{s,r,t}$ an interacted size bin-rating class-year fixed effect.[16] The vector $X_{i,t}$ contains (i) the ratio of EBITDA to total assets and (ii) the ratio of accounts receivable and inventories to total assets. Standard errors are clustered at the firm level.

The reason for not including firm fixed effects in (12) is that $\sigma_{j,t}^{EBITDA}$ is highly persistent over time and that firm or industry fixed effects therefore would absorb essentially all identifying variation in the data. By instead relying on the interacted fixed effect $\alpha_{s,r,t}$, the estimate of β captures how the utilization rates chosen by firms of similar size and creditworthiness in a given year differ depending on the cash-flow volatility they face. As before, the controls in the vector $X_{i,t}$ ensure that our estimate of β is not biased by contemporaneous firm-level cash-flow shocks, nor by differences in firms' working-capital needs. Our hypothesis is that $\beta < 0$, i.e., that higher cash-flow volatility is associated with lower utilization rates.

The estimation results are reported in Table 2. We quantify the economic significance of the estimated effects by comparing the implied average difference in utilization rates between firms operating in industries at the 90th and the 10th percentiles, respectively, of the cash-flow volatility distribution. Column (1) shows that cash-flow volatility has a statistically significant negative impact on credit line utilization rates: the difference between firms in high and low volatility

[16]The size bins used for constructing the interacted fixed effect are the same as those used throughout section 3. The rating classes comprise five bins of the distribution of firm-level probabilities of default, as estimated by the credit bureau UC AB.

Table 2: Productivity uncertainty and utilization rates

	Dependent variable: Utilization rate		
	(1)	**(2)**	**(3)**
	Current period	Max in past three months	Max in past twelve months
$\sigma_{j,t}^{EBITDA}$	–0.506***	–0.560***	–0.746***
	[0.067]	[0.075]	[0.090]
EBITDA/Total assets	–0.507***	–0.650***	–0.646***
	[0.015]	[0.017]	[0.019]
AR&I/Total assets	0.265***	0.328***	0.359***
	[0.009]	[0.009]	[0.011]
90th versus 10th percentile	–0.042	–0.047	–0.062
Size $\times$ Rating class $\times$ Year FE	Yes	Yes	Yes
Number of observations	36,295	36,295	26,917
Number of firms	13,644	13,644	12,087
Adjusted R^2	0.181	0.218	0.214

This table reports estimation results for the regression specified in (12). The unit of observation is firm-year and the sample period 2019–2022. The dependent variable is the end-of-year utilization rate in the first column and the maximum utilization rate during the past three and twelve months, respectively, in the second and third columns (i.e., during October-December and January-December, respectively). AR&I is short for accounts receivable and inventory. Standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the ten, five, and one percent levels, respectively.

industries is 4.2 percentage points, which corresponds to 19 percent of the mean utilization rate in the sample. The coefficients on the control variables have the expected signs: firms utilize their credit lines *less* when they generate more internal funds (as captured by EBITDA) and *more* when they have higher working-capital funding needs (as captured by the ratio of accounts receivable and inventories to total assets).

Columns (2)-(3) demonstrate that the magnitude of the cash-flow volatility effect is even larger for the alternative measures of utilization. More specifically, we find that the difference between firms in high and low volatility industries is 4.7 percentage points when the dependent variable is the maximum utilization rate over the past three months and 6.2 percentage points when the dependent variable is the maximum utilization rate over the past twelve months. The results in Table 2 thus confirm the model prediction that firms draw less on credit lines when they face higher uncertainty in productivity.

5.2 Financial uncertainty

Financial uncertainty in the model is captured by the dispersion of ξ, the parameter that determines the fraction of a firm's cash-flow that can be used as collateral. More specifically, the larger is the dispersion of the next period ξ, the higher is the expected cost of financial distress for any level of debt raised in the current period. An increase in the dispersion of ξ therefore induces the firm to lower its current borrowing, as established in Proposition 4.3.

Our empirical proxy for the dispersion of ξ is the maturity of a firm's credit lines. The idea is that firms have a degree of certainty about the availability and price of credit during the lifespan of their credit lines, but once the lines fall due both the price and the quantity of credit are subject to renegotiation and thus become uncertain.[17]

We test whether higher financial uncertainty is associated with lower utilization rates by estimating the following regression equation:

$$Y_{i,t} = \alpha_i + \eta_t + \beta \cdot \mathbb{1}\{Maturity_{i,t} \leq 1 \text{ year}\} + \gamma \cdot X_{i,t} + \varepsilon_{i,t}. \tag{13}$$

The dependent variable is a measure of firm i's credit-line utilization rate at the end of year t. $\mathbb{1}\{Maturity_{i,t} \leq 1 \text{ year}\}$ is an indicator variable equal to one if the weighted average remaining maturity of the firm's credit lines is less than or equal to one year at the end of year t; α_i and η_t are

[17] In practice, firms are not completely certain about their access to credit even during the lifespan of their credit lines: first, because banks have the right to renegotiate prior to maturity if the firm violates a covenant; and second, because firms are often able to renegotiate *favorable* changes to credit lines prior to maturity (Roberts and Sufi, 2009). Uncertainty nevertheless increases as a credit line nears expiry and this is what our proxy is intended to capture.

firm and year fixed effects, respectively; and the vector $X_{i,t}$ comprises the ratios of (i) EBITDA to total assets and (ii) accounts receivable and inventories to total assets. As before, standard errors are clustered at the firm level.

The inclusion of the firm fixed effects implies that we rely on within-firm variation in credit-line maturities for identification—i.e., β captures how the utilization rate of a given firm differs between years when its credit-lines have long and short maturities, respectively. The control variables in the vector $X_{i,t}$ ensure that neither contemporaneous cash-flow shocks nor variation in the firm's working capital funding needs introduce bias in the estimates. Under the hypothesis that shorter maturities are associated with lower utilization rates, we should observe $\beta < 0$.

The estimation results are reported in Table 3. Column (1) shows that the average utilization rate is 10 percentage points lower for firms with an average maturity shorter than one year. The difference is substantial considering that the average utilization rate is 23 percent in the sample.[18] Columns (2)-(3) show that the baseline result holds also for alternative measures of utilization. We find that the difference between firms with short and long maturities is 7.0 percentage points when the dependent variable is the maximum utilization rate over the past three months and 9.5 percentage points when the dependent variable is the maximum utilization rate over the past twelve months. These results demonstrate that firms facing high financial uncertainty—as measured by the remaining maturity of the credit lines—utilize their credit lines less than firms facing lower financial uncertainty.

6 Structurally derived measure of borrowing capacity

Until now we have used the undrawn amount of a firm's credit lines as a measure of its unused borrowing capacity. The concomitant measure of total borrowing capacity is the committed amount on the firm's credit lines plus other loans on its balance sheet. As emphasized earlier, however, this measure is only a proxy for the actual borrowing capacity of the firm. On the one hand, the measure overestimates the true borrowing capacity if there are restrictive covenants

[18] This finding is robust to using the initial (at-origination) maturity of a firm's credit lines as explanatory variable. More specifically, estimating (13) with the initial maturity as explanatory variable yields $\hat{\beta} = -0.073^{***}$.

Table 3: Financial uncertainty and utilization rates

	Dependent variable: Utilization rate		
	(1)	**(2)**	**(3)**
	Current period	Max in past three months	Max in past twelve months
$\mathbb{1}\{Maturity_{i,t} \leq 1 \text{ year}\}$	–0.104***	–0.070***	–0.095***
	[0.024]	[0.024]	[0.025]
EBITDA/Total assets	–0.431***	–0.518***	–0.292***
	[0.020]	[0.022]	[0.024]
AR&I/Total assets	0.281***	0.380***	0.367***
	[0.021]	[0.024]	[0.029]
Firm and year FE	Yes	Yes	Yes
Number of observations	32,700	32,700	23,518
Number of firms	10,047	10,047	8,686
Adjusted R^2	0.612	0.642	0.710

This table reports estimation results for the regression specified in (13). The unit of observation is firm-year and the sample period 2019–2022. The dependent variable is the end-of-year utilization rate in the first column and the maximum utilization rate during the past three and twelve months, respectively, in the second and third columns (i.e., during October-December and January-December, respectively). AR&I is short for accounts receivable and inventory. Standard errors clustered at the firm level are reported in square brackets. ***, **, and * denote statistical significance at the ten, five, and one percent levels, respectively.

that limit the firm's access to the credit lines. On the other hand, the measure underestimates borrowing capacity if banks are willing to increase the size of the credit line but the firm does not want it.

Recognizing that committed amounts are imperfect proxies for actual credit limits, we construct an alternative measure of borrowing capacity derived from the structural estimation of the model. Crucially, the structural derivation allows us to separate the component linked to the firm's real performance (productivity shocks) from the component that is independent of firm performance (financial shocks). We then use the latter to examine whether credit supply shocks unrelated to the firm's performance influence borrowing in the data, even when the firm is not fully utilizing its current credit capacity.

6.1 Estimation procedure

We use firm-level data to quantify the values of $z_{i,t}$ and $\xi_{i,t}$ that satisfy two structural conditions for each firm i at time t. The first condition is the per-worker earnings,

$$\pi_{i,t} = z_{i,t} - w_{i,t}, \tag{14}$$

where the subscript i indicates that the variable pertains to a specific firm i and the subscript t to a specific year.

In the empirical implementation we interpret $w_{i,t}$ as overall production costs, which include the cost of intermediate inputs in addition to the cost of labor. In the data we have firm-level measures of earnings, $\pi_{i,t}$, as well as production costs, $w_{i,t}$. Therefore, we can compute productivity as $z_{i,t} = \pi_{i,t} + w_{i,t}$.

The second structural condition is the optimality condition for the choice of debt,

$$q_t = \beta\Big[1 + \mathbb{E}_{i,t}\varphi'_{t+1}(b_{i,t+1})\Big] + \lambda_{i,t}. \tag{15}$$

The function $\varphi'_{t+1}(b_{i,t+1})$ is the marginal cost of financial distress and takes the form

$$\varphi'_{i,t+1}(b_{i,t+1}) = \eta\kappa \cdot \left(\max\Big\{b_{i,t+1} - \xi_{i,t+1}z_{i,t+1}\ ,\ 0\Big\}\right)^{\eta-1}.$$

We observe each firm's choice of debt $b_{i,t+1}$ in the data, and we get the value of productivity $z_{i,t}$ from condition (14). We can then use condition (15) to construct a sequence of $\xi_{i,t}$ for each firm once we have assigned the values of all model parameters.[19]

[19] To find the value of $\xi_{i,t}$ that solves equation (15), we need to compute the expected values of next period productivity and financial tightness, $\bar{z}_{i,t+1}$ and $\bar{\xi}_{i,t+1}$. However, once we know the parameterized stochastic process for z and ξ, the expected values are only functions of the current values, $z_{i,t}$ and $\xi_{i,t}$. Since $z_{i,t}$ has already been computed

Some of the parameter values are common to all firms while others vary across firms. The common parameters are the discount factor, β, the price of debt, q, and the distress-cost parameters η and κ. We do not estimate these parameters, as they only play a marginal role for the results. We set $\beta = 0.92$, which targets a return on equity of about 8%, and $q = 0.98$ which targets a real interest rate of about 2%. The curvature of the cost function is more difficult to pin down empirically since η plays a similar role as κ. We then set $\eta = 1.1$ but provide a sensitivity analysis in Appendix D. The parameter κ determines the severity of the distress cost and it has a direct impact on credit utilization. For its calibration we use an iterative procedure: we start by guessing its value, solve for the utilization rate chosen by each firm, and then check whether the cross-sectional average matches the target.[20] The utilization rate that enters the estimation is the *overall* utilization rate. This is defined as all loans on a firm's balance sheet (used credit lines plus other loans) divided by the sum of all loans and the undrawn portions of credit lines. We target an overall utilization rate of 0.737, which is the average in our sample.

We now describe the estimation of the firm-specific parameters. The logarithm of $z_{i,t}$ and $\xi_{i,t}$ follow independent first-order Markov processes,

$$\ln(z_{i,t+1}) = (1-\rho_i^z)\mu_i^z + \rho_i^z \cdot \ln(z_{i,t}) + \epsilon_{i,t}, \tag{16}$$

$$\ln(\xi_{i,t+1}) = (1-\rho_i^\xi)\mu_i^\xi + \rho_i^\xi \cdot \ln(\xi_{i,t}) + \varepsilon_{i,t}, \tag{17}$$

where the residuals $\epsilon_{i,t}$ and $\varepsilon_{i,t}$ are normally distributed with zero means and standard deviations σ_i^z and σ_i^ξ. The parameters μ_i^z, ρ_i^z, σ_i^z, μ_i^ξ, ρ_i^ξ, σ_i^ξ are firm-specific and, therefore, indexed by the subscript i. To compute their values for each firm we use the following procedure:

1. Guess values of μ_i^z, ρ_i^z, σ_i^z, μ_i^ξ, ρ_i^ξ, σ_i^ξ for firm i.

2. Given the observed values of earnings, production costs and borrowing for firm i, determine the sequences of $z_{i,t}$ and $\xi_{i,t}$ that solve (14) and (15).

from equation (14), condition (15) allows us to compute $\xi_{i,t}$.

[20] We do not allow κ to vary across firms because it cannot be identified separately from other parameters that are estimated for each firm, most importantly the volatility of the financial shock σ^ξ. Since this parameter plays a similar role as κ for the optimal choice of debt, σ^ξ and κ cannot be jointly identified for each firm.

3. Check whether the moments computed from the constructed series (mean, autocorrelation, standard deviation) match the theoretical moments for the parameterized processes of $z_{i,t}$ and $\xi_{i,t}$. The theoretical moments are computed from (16) and (17) using the guessed values of μ_i^z, ρ_i^z, σ_i^z, μ_i^ξ, ρ_i^ξ, σ_i^ξ. If not, restart from step 1 by changing the guessed parameter values until the computed moments are sufficiently close to the theoretical moments.

In what follows we describe in more detail steps 2 and 3.

Step 2: Compute ξ_t and z_t for given parameters. Once we have assigned all parameter values for firm i and we know the empirical counterparts of $\pi_{i,t}$, $w_{i,t}$ and $b_{i,t+1}$, we use condition (14) to solve for $z_{i,t}$ and condition (15) to solve for $\xi_{i,t}$. The empirical counterparts of $\pi_{i,t}$ and $w_{i,t}$ are EBITDA and production costs, respectively, both normalized by employment. Our measure of production costs does not only include labor, as in the model, but also the cost of intermediate inputs. Thus, $w_{i,t}$ corresponds to the total cost per unit of production, a reinterpretation that does not change the properties of the model. Productivity is then given by $z_{i,t} = \pi_{i,t} + w_{i,t}$.[21]

Once we have the sequence of $z_{i,t}$ for firm i at each time t, we can use equation (15) to compute $\xi_{i,t}$. The solution is found using a nonlinear solver. Given the parameterization of the model, the expectations $\bar{\xi}_{i,t+1}$ and $\bar{z}_{i,t+1}$ are only functions of their current values, $z_{i,t}$ and $\xi_{i,t}$. In solving equation (15), we need to check whether the solution is binding ($\lambda_{i,t} > 0$) or non-binding ($\lambda_{i,t} = 0$). We start with the binding solution and find the value of $\xi_{i,t}$ that satisfies the borrowing constraint, that is, $\bar{\xi}_{i,t+1}\bar{z}_{i,t+1} = b_{i,t+1}$. We then use the first order condition $q_t = \beta[1 + \mathbb{E}_{i,t}\varphi'_{i,t+1}(b_{i,t+1})] + \lambda_t$ to solve for the multiplier λ_t. If the multiplier is positive, the solution is binding. If it is negative, the solution is non-binding and the value of $\xi_{i,t}$ is found by solving the first order condition with $\lambda_{i,t} = 0$, that is, $q_t = \beta[1 + \mathbb{E}_{i,t}\varphi'_{i,t+1}(b_{i,t+1})]$.

Step 3: Update parameter values. Having constructed sequences of $z_{i,t}$ and $\xi_{i,t}$ for firm i, we compare their means, autocorrelations and standard deviations with the theoretical counter-

[21] Note that the cost of production $w_{i,t}$ is constant in the model, but varies over time in the data. To account for this, we measure the time-invariant cost for firm i as the average of its operating cost over time, $w_i = \frac{1}{T}\sum_{t=1}^{T} w_{i,t}$. Variation in this cost will then be re-assigned to profits $\pi_{i,t}$.

parts resulting from their parameterized processes specified in (16) and (17). The theoretical moments are functions of the guessed parameters $\mu_i^z, \rho_i^z, \sigma_i^z, \mu_i^\xi, \rho_i^\xi, \sigma_i^\xi$ as follows:

$$\begin{aligned}
\text{Mean}\Big(\ln(z)\Big) &= \mu_i^z, \\
\text{Autocorr}\Big(\ln(z)\Big) &= \rho_i^z, \\
\text{Std}\Big(\ln(z)\Big) &= \frac{\sigma_i^z}{\sqrt{1-\rho_i^{z\,2}}}, \\
\text{Mean}\Big(\ln(\xi)\Big) &= \mu_i^\xi, \\
\text{Autocorr}\Big(\ln(\xi)\Big) &= \rho_i^\xi, \\
\text{Std}\Big(\ln(\xi)\Big) &= \frac{\sigma_i^\xi}{\sqrt{1-\rho_i^{\xi\,2}}}.
\end{aligned}$$

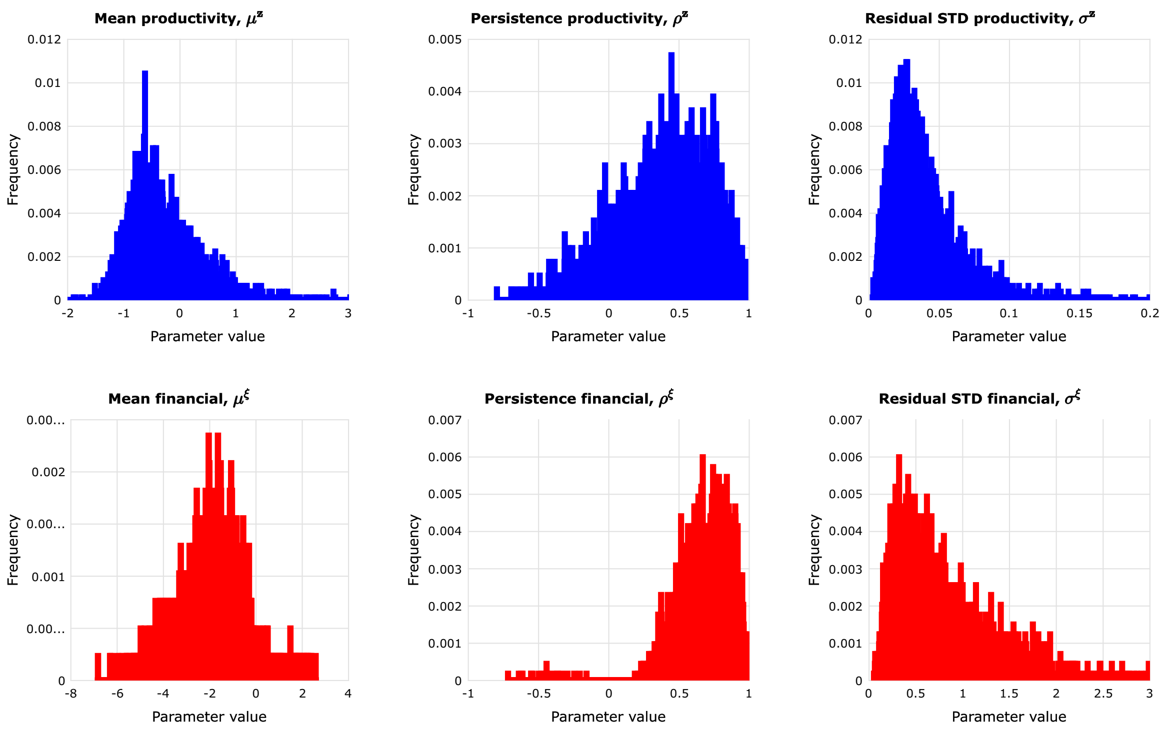
We continue to update the guessed values for the parameters $\mu_i^z, \rho_i^z, \sigma_i^z, \mu_i^\xi, \rho_i^\xi, \sigma_i^\xi$ going back to step 1 until the moments calculated from the constructed series are (approximately) equal to the theoretical moments specified here. Having repeated this procedure for each firm i, we check whether the cross-sectional average utilization rate in the sample matches the target. If the average utilization is lower (higher) than the target, we decrease (increase) the guessed value of the distress cost parameter κ and restart the procedure with the new guess. We continue updating κ until the average utilization rate generated by the model matches the target 0.737.

Since the parameters are estimated for each firm, we need reasonably long time series for each firm to obtain meaningful estimates. This implies that our credit-registry data is not suitable for the estimation because it only goes back to 2019. Fortunately, the financial accounts of most Swedish firms include information not only on the debt of a firm, but also on the undrawn amounts of credit lines. Hence, we can use our financial accounts data to measure each firm's actual choice of debt, b_{t+1}, as well as to compute the empirical proxy for its borrowing capacity.

We impose three filters to select the firms included in the estimation sample. First, to ensure that we obtain meaningful parameter estimates, we only include firms with at least 10 years of data. Second, since the exercise can be performed only for firms with positive bank borrowing, we exclude those with zero debt on their balance sheet. Finally, we exclude firms whose average earnings over the sample period are negative.

Figure 9 plots the cross-sectional distribution of parameters estimated for each firm included in the sample. The sample contains 3,786 firms, each observed for at least 10 years. The distributions of the mean values of the two shocks, μ^z and μ^ξ, are not far from being symmetric. The distributions of persistence and volatility parameters—ρ^z, ρ^ξ, σ^z and σ^ξ—display significant skewness. In particular, most firms have a high degree of persistence in productivity and financial shocks, and volatility has a long upper tail.

Figure 9: Distribution of estimated parameters



6.2 Borrowing capacity: data vs. model

From the structural estimation we obtain sequences of $z_{i,t}$ and $\xi_{i,t}$ for each firm i. Given the values of the estimated parameters we can then compute the next period expected values of these two variables at any time t, that is, $\bar{z}_{i,t+1}$ and $\bar{\xi}_{i,t+1}$. Using Equation (1), the structural estimation allows us to derive the per-worker credit capacity for each firm i as

$$\text{Credit capacity}_i = \bar{z}_{i,t+1} \cdot \bar{\xi}_{i,t+1}. \tag{18}$$

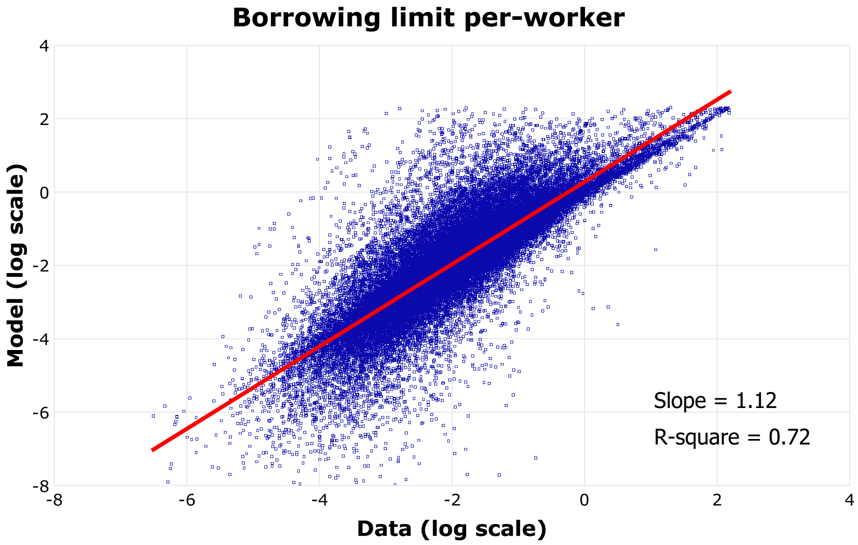
Figure 10 plots the measure of borrowing capacity derived from the structural estimation (Model) against our empirical proxy for borrowing capacity, namely, the committed amount on credit lines plus other loans on a firm's balance sheet (Data). Both variables are expressed in per-worker terms and are plotted on log scales for better visualization. The points in the graph correspond to firm-year observations and the line represents the best linear fit.

The model-derived measure of borrowing capacity is highly correlated with the empirical measure. A simple linear regression yields a slope coefficient close to one and an R^2 of 0.72, which implies that the empirical proxy for borrowing capacity explains nearly three quarters of the variation in the model-derived measure. Recall that we never use data on committed amounts in the structural estimation, but instead infer the borrowing limits as the values that rationalize the actual borrowing decisions of firms observed in the data. There is thus no guarantee that the model-derived measure of borrowing capacity should be correlated with the empirical measure based on committed amounts. The high correlation suggests that the empirical measure based on committed amounts is a reasonable proxy for a firm's actual borrowing capacity.

6.3 The response of borrowing to credit-limit changes

We now use the measure of borrowing capacity derived from the estimation of the model to test the second prediction of the model: if a firm is credit constrained in a dynamic sense, its borrowing responds to credit-limit changes even if the firm had not exhausted its borrowing

Figure 10: Borrowing capacity in the data and in the model



This figure plots the empirical measure of firms' borrowing capacity (Data) against the borrowing limits obtained from the structural estimation (Model), along with a fitted regression line. Both variables are expressed in per-worker terms and plotted on log scales. The empirical measure of a firm's borrowing capacity is the debt on the firm's balance sheet plus the undrawn amounts on its credit lines.

capacity prior to the limit change (Proposition 4.2).

We use the following regression to test how firms' borrowing decisions respond to changes in their credit limits:

$$\frac{\Delta Debt_{i,t}}{NetAssets_{i,t-1}} = \sum_{k=1}^{5} \beta^k \cdot \frac{\Delta DebtLimit_{i,t}}{NetAssets_{i,t-1}} \cdot \mathbb{1}\left\{Utilization\ bin_{i,t-1} = k\right\} + \alpha_i + \theta_{j,t} + \varepsilon_{i,t}. \quad (19)$$

The dependent variable is the observed change in the bank debt for firm i's between years $t-1$ and t. The explanatory variable is the change in the borrowing limit for firm i that is *independent* of the real performance of the firm. Both variables are scaled by the firm's net assets in year $t-1$.

To properly test our hypothesis, the changes in credit capacity $\Delta DebtLimit_{i,t}$ should not be driven by changes in the real performance of the firm. Otherwise, the estimation of Equation

(19) would capture a spurious correlation: the change in the real performance could trigger unrelated changes in both borrowing and credit capacity. Our model-based measure of credit capacity indicated in Equation (18) allows us to separate changes driven by the real performance of the firm—the variable $\bar{z}_{i,t+1}$—from changes induced by pure financial factors—the variable $\bar{\xi}_{i,t+1}$. Thus, in the estimation of Equation (19), $\Delta DebtLimit_{i,t}$ corresponds to changes in the variable $\bar{\xi}_{i,t+1}$.[22]

As far as the other terms added to the regression Equation (19), we have a firm fixed effect, α_i, an industry-year fixed effect, $\theta_{j,t}$. The firm fixed effect absorbs any time-invariant unobservable firm characteristics affecting borrowing while the industry-year fixed effect should capture any unobservable time-variation in credit demand common to firms operating in the same two-digit industry. Standard errors are clustered by firm and year.

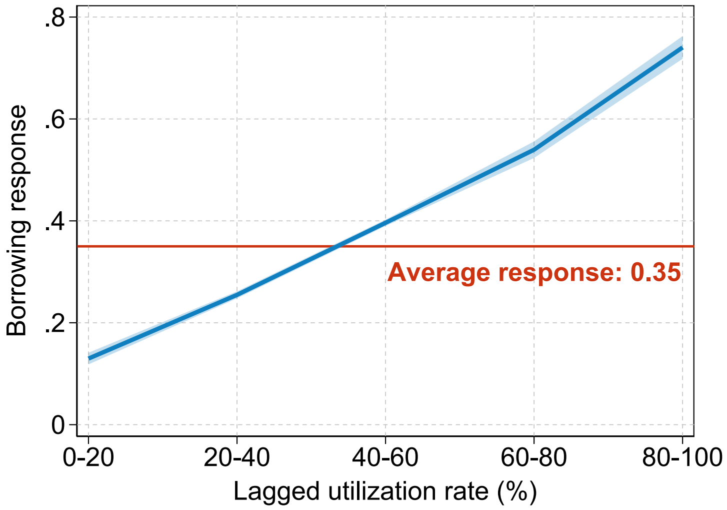
We capture heterogeneity in the response of borrowing to changes in the borrowing limit by interacting the explanatory variable with an indicator function for five bins of the distribution of utilization rates in year $t-1$. A firm's credit utilization rate is computed as its actual borrowing in year $t-1$ divided by its model-derived borrowing limit in the same year. The coefficient β^k thus captures the response of borrowing to a change in the borrowing limit for a firm whose utilization rate in year $t-1$ falls in bin k of the utilization-rate distribution.

The estimation results, plotted in Figure 11, show that increases in the borrowing limit induced by financial shocks are associated with statistically significant increases in actual borrowing in all utilization-rate bins. The response strongly decreases with the distance to the limit: following an increase in the borrowing limit of one SEK, actual borrowing increases by approximately 0.74 SEK for firms nearest the limit, by 0.40 SEK in the middle of the distribution, and by 0.13 SEK for firms furthest from the limit.[23] The average firm thus responds to an increase in its credit limit by borrowing more, irrespective of whether it had exhausted its borrowing capacity prior to the limit change. The evidence is thus consistent with the view that many firms face

[22] Even though the estimated credit capacity is derived using data for the firm's debt, this does not guarantee that $\bar{\xi}_{i,t+1}$ is positively correlated with the firm's debt. For example, if changes in credit capacity are mostly driven by changes in $\bar{z}_{i,t+1}$, the constructed variable $\bar{\xi}_{i,t+1}$ could be uncorrelated or even negatively correlated with the firm's debt.

[23] Estimating a version of (19) in which the explanatory variable is not interacted with the utilization-rate bins yields $\beta = 0.35^{***}$—i.e., borrowing on average increases by 0.35 SEK for every SEK increase in committed amount.

Figure 11: The effect of limit changes on firms' borrowing



This figure plots the estimates of β^k from the regression specified in (19). The shaded area represents 95-percent confidence bands, computed on the basis of standard errors clustered by firm and year.

tight dynamic credit constraints, and that this contributes to the overall low utilization of credit observed in the data.

6.4 Shock decomposition

Another benefit of a structural estimation is that we can use the model to conduct counterfactual exercises, particularly to quantify how the two shocks—capturing, respectively, real and financial conditions—contribute to credit utilization. To do so, we conduct two exercises.

In the first exercise, we compute the optimal borrowing chosen by the firm if the productivity shock $z_{i,t}$ is the only stochastic driver of the firm's dynamics. This is done by setting $\sigma_i^{\xi} = 0$, so that $\ln(\xi_{i,t})$ is not stochastic and remains constant at the average value μ_i^{ξ}. We then simulate the model with the sequence of $z_{i,t}$ that we constructed from the structural estimation described in subsection 6.1. In the simulation we solve for the optimal decisions of each firm at time t, given the current realization of $z_{i,t}$. Importantly, the optimal policies are derived under the assumption that firms know that $\xi_{i,t}$ remains constant over time, while $z_{i,t}$ is stochastic.

In the second counterfactual exercise, we set $\sigma_i^z = 0$, so that $\ln(z_{i,t})$ remains constant at the average value μ_i^z. In this case, the firm changes its optimal borrowing only in response to $\xi_{i,t}$, which, in the simulation, takes the values imputed from the structural estimation. When solving for the optimal policies, firms know that $z_{i,t}$ will remain constant over time while $\xi_{i,t}$ is stochastic. The average cross-sectional utilization in the two counterfactual exercises is reported in Table 4.

Table 4: Contribution of productivity and financial shocks to credit utilization

	Both $z_{i,t}$ and $\xi_{i,t}$ stochastic	Only $z_{i,t}$ stochastic	Only $\xi_{i,t}$ stochastic
Average utilization	0.737	0.997	0.762

The first column reports the average utilization rate for the baseline case with both shocks active. By construction, the optimal borrowing chosen by each firm in the baseline case coincides with the debt observed in the data for the firm. Remember that parameters are estimated to replicate the debt observed in the data for each firm. In this case, the average utilization is 73.7 percent, which we imposed in the estimation as a target.

The second column presents the results for the counterfactual exercise with only productivity shocks. By shutting down the financial shock, the average utilization rises to 99.7 percent. Conversely, when we shut down productivity shocks (third column), the average utilization is 76.2 percent. This shows that the risk associated with shocks more directly related to the financial condition of the firm plays a much more important role in keeping firms away from the borrowing limit. This highlights the importance of financial shocks, complementing existing studies in macro-finance (such as Jermann and Quadrini (2012) and Monacelli, Quadrini and Trigari (2023)) and micro-finance (such as Quadrini and Sun (2018)).

To summarize, the main finding of this section is that financial market risk seems to be the dominant factor explaining the low utilization of credit observed in the data. Operational uncertainty, captured in the model by revenue fluctuations, does not seem to play a very important role. This conclusion, however, should be interpreted with caution because the financial shock

ξ could also capture anticipated future productivity changes that may not be fully incorporated into current productivity z_t.

7 Final remarks

We have presented a set of stylized facts showing that firms, both small and large, have access to considerable amounts of reasonably priced borrowing via credit lines. However, they choose not to fully utilize the available credit. These facts could be consistent with the view that credit constraints are widespread if we take into account that the financial decisions of firms are dynamic and reflect future uncertainty (dynamic credit constraints).

To illustrate this point, we have developed a simple theoretical model where firms face a trade-off in the choice of borrowing: the current benefit of higher debt vs. the higher expected cost of future illiquidity. This leads them to optimally choose to borrow less than the limit in order to preserve spare borrowing capacity for the future. In such an environment, lower utilization of credit can be a consequence of tighter dynamic credit constraints rather than an indicator of credit slackness.

We tested, with positive outcomes, two predictions of the model: (i) credit utilization declines with operational and financial uncertainty, and (ii) firms borrow more after a credit limit increase, even if credit was underutilized prior to the increase. The structural estimation of the model was instrumental for the empirical tests, as it allowed us to derive firm-level measures of credit limit shocks.

APPENDIX

A Proof of Proposition 4.2

Denote by $x = \xi z$ the product of the two shocks and $\Gamma(x)$ the joint cumulative probability density defined in the domain $[x_{Low}, x_{High}]$. Assume that the density function is strictly increasing in x. The expectations of the distress cost and its derivative can be written as

$$\mathbb{E}\varphi(b) = \kappa \cdot \int_{x_{Low}}^{b} (b-x)^2 \Gamma(\mathrm{d}x), \tag{20}$$

$$\mathbb{E}\varphi'(b) = 2\kappa \cdot \int_{x_{Low}}^{b} (b-x) \Gamma(\mathrm{d}x). \tag{21}$$

Both terms are strictly increasing in $b \geq x_{Low}$. A condition that is always satisfied. In fact, if $b \leq x_{Low}$, then $b_{t+1} \leq \bar{\xi}_{t+1}\bar{z}_{t+1}$, that is, the borrowing constraint is not binding and $\lambda_t = 0$. Since $\mathbb{E}\varphi'(b)$ is also zero, condition (10) cannot be satisfied under the assumption $q_t > \beta$.

If the borrowing constraint is binding, then $b_{t+1} = \bar{\xi}_{t+1}\bar{z}_{t+1}$. For this to be the case we need

$$q_t > \beta \mathbb{E}_t \Big[1 + \varphi'_{t+1}(\bar{\xi}_{t+1}\bar{z}_{t+1}) \Big],$$

that is, if we set the debt equal to the borrowing limit, condition (10) implies $\lambda_t > 0$. But for sufficiently high values of κ we will have

$$q_t < \beta \mathbb{E}_t \Big[1 + \varphi'_{t+1}(\bar{\xi}_{t+1}\bar{z}_{t+1}) \Big].$$

Therefore, for sufficiently high values of κ, the borrowing constraint is non-binding, that is, $b_{t+1} < \bar{\xi}_{t+1}\bar{z}_{t+1}$. On the other hand, if $q_t = \beta$, the only way condition (10) can be satisfied is to have $\lambda_t = \mathbb{E}_t \varphi'_{t+1}(b_{t+1}) = 0$, which requires $b_{t+1} \leq x_{Low} < \bar{\xi}_{t+1}\bar{z}_{t+1}$. Thus, the borrowing constraint is never satisfied and the distress cost is always zero.

Next we need to show what happens if $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ increase. Consider an increase $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ that shifts the distribution to the right without changing its shape. This relaxes the borrowing constraint and reduces the values of $\mathbb{E}_t\varphi'_{t+1}(b_{t+1})$ as we can see from (21). Therefore, condition (10) implies that b_{t+1} must increase.

We can now turn to condition (11). We want to show that the left-hand-side increases when $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ increase. If we can prove that, then we prove that $\Upsilon'(g_{t+1})$ on the right-hand-side must also increase and this is possible only if g_{t+1} increases.

To show that the left-hand-side of (11) increases with $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$, let's first consider the case in which the debt b_{t+1} does not change. In this case, an increase in $\bar{\xi}_{t+1}$ reduces $\mathbb{E}_t\varphi_{t+1}(b_{t+1})$, raising the left-hand-side of (10). If $\bar{z}_{t+1}$ increases, $\mathbb{E}_t\hat{v}_{t+1}$ rises and $\mathbb{E}_t\varphi_{t+1}(b_{t+1})$ falls. Thus, both effects raise the left-hand-side of condition (11).

We now allow the debt to change. We have seen that condition (10) implies that an increase in ξ_{t+1} or z_{t+1} raises b_{t+1}. We now show that an increase in b_{t+1} does not reduce the left-hand-side of equation (11). Taking the derivative of the left-hand-side we obtain

$$q_t - \beta - \beta\mathbb{E}_t\varphi'_{t+1}(b_{t+1}).$$

Condition (10) implies that this term is non-negative. Therefore, an increase in b_{t+1} induced by a higher value of $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ cannot reduce the left-hand-side of (11). Together with the direct effect characterized above (keeping the debt constant), this establishes that a higher value of $\bar{\xi}_{t+1}$ or $\bar{z}_{t+1}$ increases the left-hand-side of (11). The right-hand-side must then also rise, which requires a higher value of employment growth g_{t+1}. ■

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INTERNET APPENDIX

A Computing covenant-adjusted measures of credit-line size and utilization

In this section, we describe the computation of the covenant-adjusted measures of the size and utilization of credit lines presented in Section 3.1 of the paper. The basic idea is to adjust the committed amount on a firm's credit lines downwards until the undrawn amount equals the increase in borrowing that the firm can undertake without breaking any covenant. We do not observe covenants in the data and therefore follow the covenant-adjustment approach of Greenwald, Krainer and Paul (2020). This involves assuming (i) that all firms are subject to two of the most common covenants in debt contracts—a minimum interest coverage ratio and a maximum debt-to-earnings ratio—and (ii) that the requirements on these ratios equal the average requirements in the sample of debt contracts studied by Greenwald (2019).

The interest-coverage (IC) covenant is defined as

$$\frac{\sum_{k=-3}^{0} EBITDA_{i,t-k}}{\sum_{k=-3}^{0} IntExp_{i,t-k}} \geq \kappa, \tag{A1}$$

where k denotes quarters and the summation reflects that the IC covenant is typically evaluated based on rolling four-quarter sums of cash flow and interest expenditures. The IC covenant thus requires that the ratio of operational cash flow (EBITDA) to interest expenditures exceeds κ. The debt-to-earnings (DE) covenant is defined as:

$$\frac{Debt_{i,t}}{\sum_{k=-3}^{0} EBITDA_{i,t-k}} \leq \tau, \tag{A2}$$

where EBITDA like before is measured as a four-quarter rolling sum and debt is the firm's total interest-bearing debt in period t. The DE covenant thus requires the ratio of debt to operational cash flow to debt to be below τ. Following Greenwald, Krainer and Paul (2020), we assume that all firms face thresholds of $\kappa = 2.75$ and $\tau = 3.75$, respectively.

The first step in the adjustment procedure is to compute the covenant-adjusted undrawn amount on a firm's credit lines. We define this as the minimum of the actual undrawn amount and the largest increase in debt that the firm can undertake without breaking any covenant:

$$Undrawn_{i,t}^{CovAdj} = \min\left\{Undrawn_{i,t}, Undrawn_{i,t}^{IC}, Undrawn_{i,t}^{DE}\right\}. \tag{A3}$$

The maximum increase in debt that the firm can undertake without breaking the respective covenants are, in turn, computed as

$$\begin{aligned} Undrawn_{i,t}^{IC} &= \max\left\{\frac{\sum_{k=-3}^{0} EBITDA_{i,t-k}}{2.75 \cdot i_{i,t}} - \frac{\sum_{k=-3}^{0} IntExp_{i,t-k}}{i_{i,t}}, 0\right\} \\ Undrawn_{i,t}^{DE} &= \max\left\{3.75 \cdot \sum_{k=-3}^{0} EBITDA_{i,t-k} - Debt_{i,t}, 0\right\}, \end{aligned} \tag{A4}$$

where $i_{i,t}$ is the weighted average interest rate on firm i's credit lines in period t. When the credit-line interest rate is missing for a firm-period observation, we impute it as the average in the industry $\times$ size decile $\times$ period$\times$ risk-class cell to which the observation belongs. We bound the covenant-adjusted undrawn amounts at zero, so that the measures reflect the maximum *additional* amount of borrowing that the firm is able to undertake.[A1]

We then define the covenant-adjusted committed amount on a firm's credit lines as the sum of the actual drawn amount and the covenant-adjusted undrawn amount:

$$Committed_{i,t}^{CovAdj} = Drawn_{i,t} + Undrawn_{i,t}^{CovAdj}. \tag{A5}$$

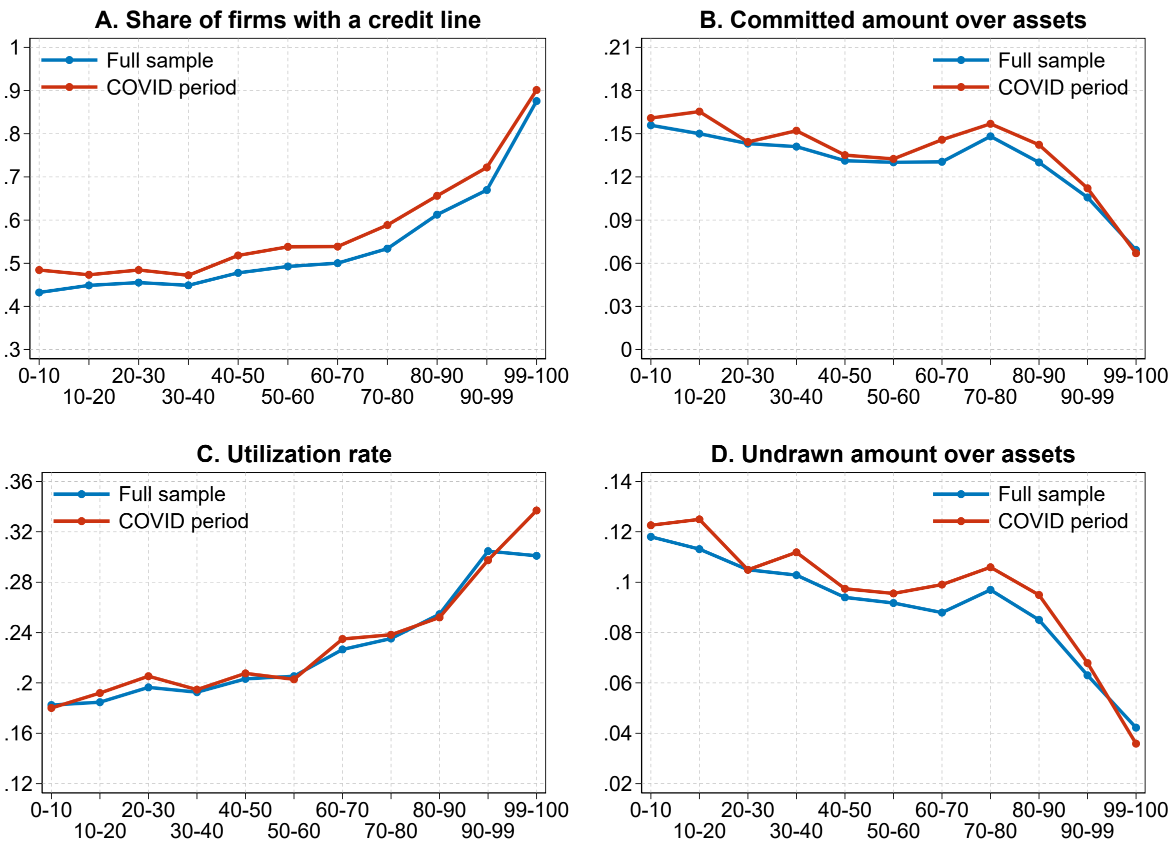
Finally, we compute the various covenant-adjusted measures of the size and utilization of credit lines based on $Committed_{i,t}^{CovAdj}$ and $Undrawn_{i,t}^{CovAdj}$; for example, we measure the covenant-adjusted utilization rate as $Used_{i,t}^{CovAdj} = Drawn_{i,t}/Committed_{i,t}^{CovAdj}$.

[A1] We are in practice forced to rely on fiscal-year figures for EBITDA and interest expenditure from the latest available annual report when computing the measures in (A4), as most firms in our data do not report quarterly financial accounts.

B Additional tables and figures

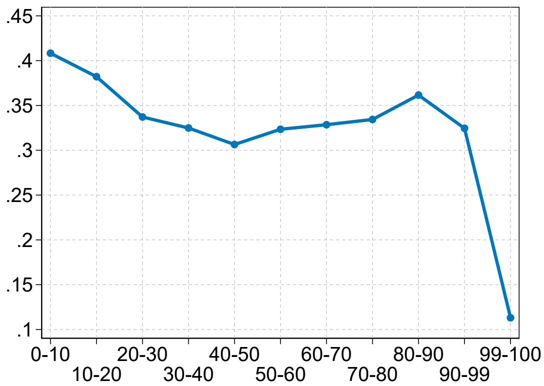
Figure B1 plots the main credit-line characteristics from Figure 4 separately for the full sample period and the COVID period (March 2020 to September 2020). Figure B2 shows how the average utilization rate on credit lines varies over the size distribution when the sample is restricted to firms that have credit lines with committed amounts of at least 10 million SEK (roughly one million USD). Figure B3 shows the ratios of cash holdings to assets and undrawn credit lines to assets, respectively, for firms with credit lines (Panel A), as well as how the ratio of total liquidity (cash holdings plus undrawn credit lines) to assets varies across firms with and without credit lines (Panel B).

Figure B1: Comparing the full sample to the COVID period



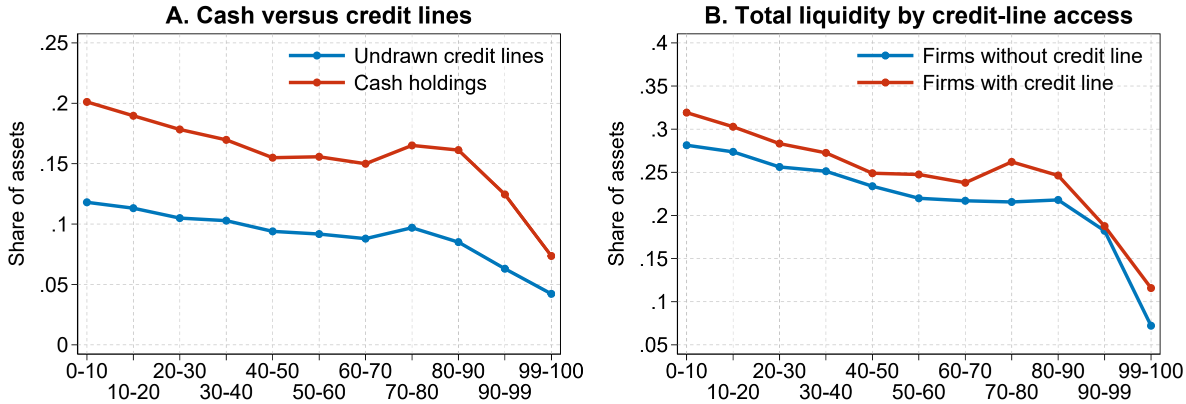
This figure plots the averages of various credit-line characteristics within each bin of the net-asset distribution for the full sample (blue line) and the COVID period (red line). The COVID period spans March 2020 to September 2020. Panel A is based on all firms in the sample, whereas Panels B-D concern firms that have at least one credit line from a bank.

Figure B2: Utilization rates over the size distribution for the restricted sample



This figure plots the average utilization rate on credit lines within each percentile of the firm-size distribution when implementing the same sample restriction as in the Federal Reserve's Y-14 data set, namely, only including loans with at least 10 million SEK (roughly $1 million) in committed amount.

Figure B3: Unused credit lines and cash over the size distribution



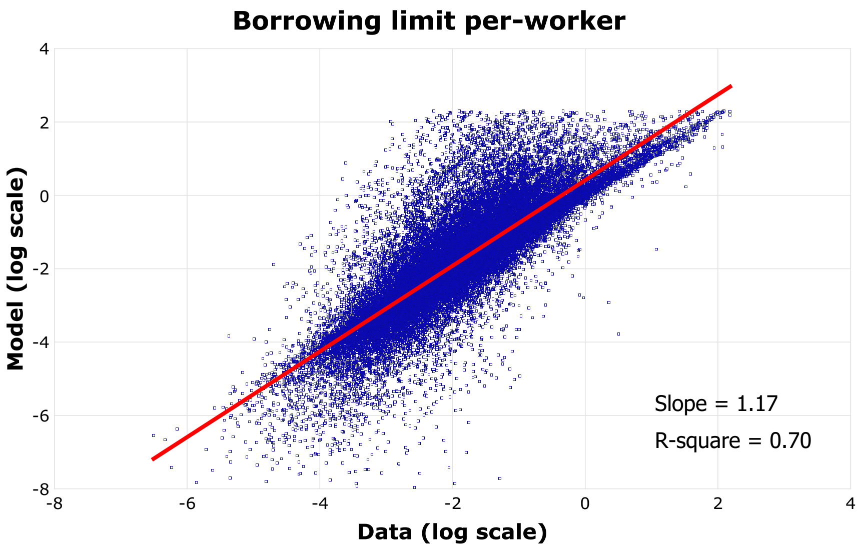
Panel A shows the average ratios of undrawn credit lines to assets (blue line) and cash holdings to assets (red line) in each bin of the size distribution, when the sample is restricted to firms that have at least one credit line. Panel B plots the average ratio of total liquidity to assets for firms with and without credit lines, respectively, in each bin of the size distribution. Total liquidity is defined as the sum of cash holdings and undrawn credit lines.

D Sensitivity to the curvature of the distress cost function η

As observed in footnote 20, the curvature of the distress cost function is difficult to pin down empirically since η plays a similar role to the parameter κ, which is estimated. To illustrate the role of η, we conduct a sensitivity analysis by re-estimating the model after increasing η to 1.2 (in the baseline case, η was 1.1).

Figure D1 plots the empirical measure of firms' borrowing capacity (Data) against the borrowing limits obtained from the structural estimation (Model), but with $\eta = 1.2$. This is equivalent to Figure 10, where the model was estimated with η pre-set to 1.1. The two figures are very similar.

Figure D1: Borrowing capacity in the data and in the model when $\eta = 1.2$



This figure plots the empirical measure of firms' borrowing capacity (Data) against the borrowing limits obtained from the structural estimation (Model) with $\eta = 1.2$, along with a fitted regression line. Both variables are expressed in per-worker terms and plotted on log scales. The empirical measure of a firm's borrowing capacity is the debt on the firm's balance sheet plus the undrawn amounts on its credit lines.

Table D1 shows the contribution of the two shocks (real and financial) to the utilization of credit when the model is estimated with the new value of $\eta = 1.2$. This is the equivalent to Table

4 but with the higher value of η. In this case, we also see very minor differences.

Table D1: Contribution of productivity and financial shocks to credit utilization when $\eta = 1.2$

	Both z_t and ξ_t stochastic	Only z_t stochastic	Only ξ_t stochastic
Average utilization	0.731	0.996	0.737

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