Access to Credit and Short-Term Liquidity Sprint: Evidence from the European Labour Market

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Abstract

Corporate credit lines have remained an indispensable source of short-term liquidity management, particularly across the European financial landscape. We provide novel empirical evidence that in the first quarter of 2022, the outstanding funds acquired via the credit lines by European companies reached €87bn, accounting for 5.15% of their total assets. Our study first provides a causal identification to explain corporate credit line drawdown decisions as a response to unexpected shortfalls in the realized earnings. We show that drawdowns increase by an average of 3.17 percentage points, measured in terms of credit line drawdowns scaled by the total assets, in response to a one percentage point (unanticipated) decline in the corporate earnings to their total assets. We further investigate the comprising components of company earning outcomes and show that the inelastic nature of labour in generating corporate earnings during the 2020:Q2 provides an alternative causal identification framework to trace exogenous shocks to the labour initially towards earning outcomes and to subsequently measure the corresponding variations on the drawdown decisions. The results remain consistent with the earlier findings, where the quantity of reliance on corporate credit lines is shown to be 3.34 percentage points given a change in the earning realizations for the companies with higher exposures to labour shocks while consistently establishing no credit drawdown result for companies with lower exposures to the shock.

JEL Classification: G21, G32, G33.

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1 Introduction

Over the past decade, corporate credit lines have channelled an average of €200.87bn each year between the companies and their lending intermediaries within the European companies (Euro Area). Corporate credit lines show that in the first two quarters of 2022, the outstanding funds acquired via the credit lines reached €87bn (accounting for 5.15% of company total assets in 2020:Q2), providing companies with a substantial liquidity buffer against unexpected shocks or alternatively to finance investments.[1] Whilst alternative financing channels often co-exist alongside the credit lines to fulfil these objectives, the on-demand nature of drawdowns has consistently positioned credit lines as a quintessential financing channel for business operations and with significant implications for financial stability.

In this paper, we develop a causal framework to incorporate the relevant financial and economic considerations from a company perspective to access their corporate credit line drawdowns. Our framework first takes the credit supply settings as given and examines the extensive margins drawn as a response to transitory and unexpected shortfalls in the earning outcomes. We first examine specifically how a company is funded and how the funding raised from a corporate credit line is then used either according to the precautionary motive to provide additional resources in anticipation of liquidity risks or alternatively to support realized and pressing short-term liquidity requirements. We provide empirical evidence that companies' reliance on corporate credit lines is explained simultaneously by their short- and long-term financial indicators, where specifically companies with low net long-term assets (long-term assets less the long-term liabilities) are adversely impacted by unexpected shocks to their short-term earning outcomes, rely heavily on liquidity provision via the credit lines to finance maturing financial contracts and wages. We provide empirical evidence that companies with steady net long-term assets rely on their corporate credit lines on a precautionary basis whilst also maintaining alternative liquidity resources. Second, to establish a causal framework, our study considers a regression discontinuity design (RDD) to assess credit drawdown decisions at a narrow neighbourhood around the zero-earning threshold and shows that unexpected (marginally) negative earning outcomes causally explain significant increases in the credit drawdown decisions. Furthermore, given the scope of the study that spans the pandemic era, we investigate the causal drivers of the corporate credit line drawdowns and exploit the inelastic nature of the labour in generating

[1]The average credit line to total assets ratios rose from 4.72% in 2020:Q1 to 5.15% in 2020:Q2 (average of 7.00% during 2020:Q2-Q3). Acharya et al. (2020) documents similar empirical evidence for US companies.

real outcomes within the corporate operations to show that unexpected exogenous shocks to labour supply and labour productivity initially are transmitted to the corporate earning outcomes, which subsequently are translated to drawdown decisions. We argue that both the RDD and exploiting the inelastic nature of labour as an instrument provide valid empirical identification frameworks to trace the causal drivers of drawdown decisions through the financial and economic fundamentals.

Corporate credit lines provide two primary services to companies, including liquidity management, in light of pressing and realized requirements, and alternatively, as a (liquidity) risk management device to buffer against likely future shocks. More specifically, Campello et al. (2011) provides empirical evidence that companies rely on the drawdown as a primary source of external financing channels, whereas Acharya et al. (2012) and Acharya & Steffen (2020) extends this finding and provides further evidence on the correlations between credit lines and cash holding. From an empirical perspective, credit lines and related financial and operational indicators are endogenously driven. Brown et al. (2021) proposes a novel framework where corporate credit line drawdowns are explained by exogenous (weather) shocks, providing a causal identification to attribute changes in the drawdowns as responses to the company non-fundamentals. Nevertheless, the existing literature provides a limited basis for distinguishing between liquidity versus liquidity risk management purposes. We argue that examining the impact of fundamentals as the causal drivers of credit drawdowns provides a consolidating framework to distinguish between the aforementioned motives. Using the pandemic shock in 2020:Q2 as an exogenous shock with a primary impact on labour, we study the credit line usage of companies in the Eurozone. While the inherent nature of the shock shares a common basis in impacting labour across the regions in the study, the country-level heterogeneity across the enforcement of restrictions on labour supply enables the empirical framework to examine the financing decisions in response to labour as a fundamental factor to determine the drawdown decisions. Furthermore, our study exploits the industry-level idiosyncratic variations in terms of labour productivity to identify the variations in the drawdown decisions. This setup generalizes the framework presented in Brown et al. (2021) with a quasi-experimental setting to examine the impact of company fundamentals on credit line drawdowns, particularly due to the inelastic nature of labour during the 2020:Q2 shock where companies were unable to replenish the loss of labour supply and its productivity in the short-term. We argue that subsequent adjustments following the initial impact of the shock were adopted; however, the immediate shock to companies, initially through labour and subsequently to earnings outcomes, provides a valid identification for investigating drawdown decisions.

We show that financially unconstrained (European) companies, at the peak of the 2020:Q2 shock, substantially drew down from their credit lines after experiencing a sharp drop in their cash flows. Our results hold at the company level and when we extend our analysis to country and industry levels. This extension of our analysis to the industry level enables us to examine whether the heterogeneity of company exposure to the 2020:Q2 shock matters for liquidity risk management. This is a novel contribution to our paper as it has yet to be studied in the literature. We show that companies (in countries and industries) highly exposed to the 2020:Q2 shock drew down credit lines and accumulated cash. These new results complement the recent literature on corporate credit line drawdowns during the 2020:Q2 shock (Acharya et al. 2020) by incorporating a new risk dimension to assess the impact of company fundamentals on financing decisions. The results have important policy implications to inform corporate liquidity management across countries when shocks impact company fundamentals. For example, Acharya et al. (2013) shows that shocks increasing aggregate risk affect the supply of credit insurance. However, our results suggest that for the 2020:Q2 shock, banks supplied the requested credit insurance to companies, despite the severity of the short-term shocks, when the net long-term assets warranted extending the credit. One alternative possibility for our results is that the type of shock affecting companies matters to understanding why companies draw down credit lines and why banks supply credit. Another possibility is that central bank intervention (or announcement) effectively reduced banks' funding costs, and banks have accommodated credit demand when the long-term net assets warranted the credit extension, which forms an important agenda for future research.

While there are several strands of literature in the US on managing liquidity risk via credit insurance, there is limited work focused on European companies. This is despite their higher dependence on institutional credit than that of the US companies. Our study fills this gap in the existing literature by constructing cross-country empirical evidence on European companies and examining the functions and drivers of corporate credit line drawdowns. Figure (6) shows the total amount (in billions of euros) via credit line drawdowns by European companies across different sectors in 2020:Q2. Contrary to alternative reports, we estimate that a total of €87bn was supplied via credit lines between 2020:Q1 and 2020:Q2, and the most prominent part, €49bn, was withdrawn from credit lines in 2020:Q2 alone. There is extensive literature on credit insurance and liquidity risk management, including Shockley & Thakor (1997) and Holmström & Tirole (1998), which develop a theoretical framework to explain the difference between credit lines financing and debt in that credit lines provide an insurance device, allowing companies to access credit at the time they need it the most. Sufi (2009) provides empirical evidence on the substitution effect between internal (cash holdings) and external (credit lines) financing channels and argues that companies with higher cash balances rely less heavily on their corporate credit lines. However, these findings pertain to prior to 2008, when credit was abundant. Companies that used their credit lines were shown to be generally profitable in tandem with the credit cycles, while not-profitable companies found it difficult to access credit when they required liquidity. Acharya et al. (2014) complements this finding and explains why banks revoke credit lines to unprofitable companies and argue that banks use covenants to monitor liquidity management decisions carried out by their borrowers, with prominent results indicating that companies using credit lines have lower liquidity risk than the ones using cash holdings. Campello et al. (2011), using data for the 2008 financial crisis and US companies, shows a substitution effect between cash holding and credit lines when companies face a severe credit shortage. We complement this literature in several ways, primarily by presenting an empirical identification on the basis of an exogenous shock and separately through the impact of labour on determining financing decisions. We also employ an empirical identification approach to be able to focus on short-term liquidity risk management, and we provide robust evidence that banks and companies cooperate during the 2020:Q2 shock according to the status of net long-term obligations.

Acharya et al. (2020) show that US companies borrowed a significant amount of funds from their credit lines in March 2020. They also show that companies using credit lines were, at least at the beginning of the period, financially less constrained. We complement these results on the basis of the 2020:Q2 shock that led to a policy response across Europe. Social distancing policies across European countries were different in terms of intensity and enforcement. We argue that the heterogeneity across social distancing policies contributed to the financing decisions and, in particular, liquidity management emerging as a form of panic borrowing. We are not aware of other studies investigating these issues at the crossroads of credit lines within corporate finance and labour with a particular focus on European companies.

The subsequent parts of the study are organized in the following way. Section (2) provides an overview of the data, related empirical evidence, and a descriptive analysis of the corporate credit lines and their associated characteristics. Section (3) extends these stylized characteristics, with a particular emphasis on the study's empirical evidence to establish unexpected shortfalls as a causal driver of the corporate drawdowns and their measurements and discusses the liquidity management implications. Section (4) further examines the results provided and investigates the real inputs as the drivers of corporate earnings, which subsequently impact the drawdown decisions. Sections (3) and (4) each provide an empirical identification framework and examine the implications of financing provided through the corporate credit lines for companies' liquidity management, whereas Section (5) extends these findings to consider a wider range of economic and operational considerations that collectively predict companies financial decisions including both the short- and long-term drivers. Section (6) concludes.

2 Corporate Credit Line Characteristics

Corporate credit lines have been a universal funding channel for enterprises since the 1970s. While institutions rely on alternative non-credit-based financing channels, credit lines have maintained a persistent role between the borrower and their lending institutions. This section is motivated to provide a consolidated excerpt that describes the institutional setting surrounding corporate credit lines and highlights the credit line characteristics as distinct from their alternative channels. The definition of corporate credit lines or Revolving Credit Facility (RCF) is formally stipulated by the legal agreement to provide the principal amount over a term to the borrower with a revolving nature. The agreement refers to the maximum sum available to the borrower as the commitment that the credit institution is obliged to advance to the borrower upon drawdowns. The credit institution, therefore, charges a fee proportional to the undrawn capacity to maintain available resources upon demand.[2] Bank lines of credit and cash holdings are the two most popular liquidity management tools used by corporations (Lins et al. 2007). Sufi (2009) and Acharya et al. (2012) find that 85% of companies in their samples obtained a line of credit between 1996 and 2003, and the line of credit represents an average of 16% of book assets. In Lins et al. (2010)'s international sample, the median line of credit is equal to 15% of book assets, whereas cash holdings comprise only 9% (among which only 40% are not tied up for day-to-day operations). The theory literature considers lines of credit as committed liquidity insurance (Boot et al. (1987); Berkovitch & Greenbaum (1991); Duan & Yoon (1993); Holmström & Tirole (1998); Himmelberg et al. (1995); Shockley (1995); and Thakor (2005) show that depository banks have a natural advantage in providing liquidity under lines of credits (Kashyap et al. (2002); Gatev & Strahan (2006), Gatev & Strahan (2009); Nini (2008); Gatev et al. (2009)). The empirical literature on corporate cash holdings finds that companies, and in particular

[2] This feature is different from an informal credit line where the provision of funds is not legally binding.

smaller firms, rely heavily on cash for liquidity management (Opler et al. (1999), Almeida et al. (2004), Faulkender & Wang (2006); and Duchin et al. (2010)), suggesting that lines of credit do not provide sufficient liquidity insurance for all companies. Sufi (2009) finds that banks provide credit lines that are contingent on the maintenance of cash flow and that lines of credit are, therefore, an imperfect liquidity substitute for companies with unsteady, existing or expected cash flows.

While credit lending services form a revenue basis for lending institutions, the legal obligation associated with the maximum credit commitments embodies a tangible risk to lending counterparties. In particular, credit services are considered a stable revenue source when the default likelihood across the borrowers remains low or alternatively during economic expansions. In contrast, during an episode of economic downturn with a rising aggregate default probability and higher realized bankruptcies across the non-financial sector, credit facilities are considered primarily a risk factor to the lending institutions. Risk assessment associated with credit facilities, therefore, has to be considered from both financial and accounting standpoints. Particularly, from an accounting standpoint, credit facilities are defined in two parts: the actual drawn or granted balances are defined as liabilities and assets to the borrowers and lenders, respectively. On the other hand, the undrawn capacity is considered an off-balance sheet legally binding commitment by lending institutions, which often may be curtailed during a liquidity crunch.

Covenants, similar to alternative contracts, impose additional obligations on the borrower (and in part on the lender) for the duration of the agreement. These terms are implemented to provide the lender with relevant information and set conditions for the borrower's operations upon drawdowns. Given the unsecured nature of the agreement, the borrower often agrees to an essential and frequently added term known as the negative pledge clause to prevent alternative creditors of the enterprise from being given higher seniority than that given to their credit facility agreement. Alternatively, performance-based covenants are written to further maintain the credit quality of the borrower upon the agreement's initiation. Lian & Ma (2021) and Drechsel (2023) show that debt covenants, which are constraints proportional to a borrower's earnings or EBITDA outcome, are considered more effective terms when compared to the traditional leverage limits. Greenwald et al. (2019) studies the implications of interest coverage covenants associated with credit facilities for a borrower's future liabilities structure, investments and performance. The aforementioned covenants serve important roles within the broader market- and industry-level settings surrounding credit facilities. From a market perspective, covenants that limit a borrower's ability to increase unsecured debt, either in the form of extending existing credit lines or by seeking additional creditors, provide pro-cyclical constraints that tighten according to lower expected earnings and higher cost of finance, particularly during adverse macroeconomic shocks. However, such constraints may also dampen the real economic performance by mechanically disrupting the flow of funds to the real sector.

The construction of credit line data, financial information and relevant company characteristics require several sources described in Table (A1). The data spans 2018:Q4 and 2020:Q3. This study acquires the information on corporate credit lines from Bloomberg, including the total amount of committed credit lines, the total available credit lines, and credit line usage. The total credit line refers to the maximum amount of committed lines of credit available to a company. Typically, it contains the drawn and the undrawn credit lines. We use the available credit line as a proxy for the undrawn credit line. We calculate the drawdown quantity as the total committed line capacity less the available credit line.[3] For credit line usage, we divide credit line drawdowns by the total committed credit line capacity. We supplement credit line data by including company financial variables from Bloomberg, with all financial data measured in euros. We obtain these data for all the companies with available information for 2018:Q4 and 2020:Q3 duration. We exclude the financial sector companies, including banks, investment and insurance companies, private equity companies, security and commodity exchange and wealth management companies and focus on companies within the Euro area. The industry classification used in this paper is based on the Bloomberg Industry Classification System (BICS).[4] We match this industry classification with the North American Industry Classification System (NAICS). Then, we merge our data with O*Net for investigating the 2019 pandemic industrial exposure, based on literature (namely, Dingel & Neiman (2020), Adams-Prassl et al. (2020), Campello et al. (2020)).[5] There are 324 non-financial companies, forming an unbalanced dataset where companies are incorporated in 15 different countries. The countries with the largest number of companies are Finland (33.74%), Germany (26.75%), Italy (7.16%), Spain (6.47%), and France (6.13%). Although

[3] The available credit line is the remaining amount that a bank (financial institution) has agreed to lend.

[4] Standard Industry Classification (SIC) and North American Industry Classification System (NAICS) codes are only sparsely reported by Bloomberg. Thus, we use the industry classification code reported by Bloomberg.

[5] The O*NET system is maintained by a regularly updated database of occupational characteristics and worker requirements information across the US economy. It describes occupations in terms of the required knowledge, skills, and abilities, as well as how the work is performed regarding tasks, work activities, and other descriptors. Since Europe, especially the European Union, has an industrial distribution similar to the US, we use this database as a proxy for European industrial distribution. In order to merge this database with Bloomberg, we match BICS Level-1 Sectors and Level-3 Industry Groups with NAICS 2-digit and 3-digit sectors, respectively. We even use NAICS 4-digit sectors to ensure the accuracy of matching. Then, following Dingel & Neiman (2020), we use the labour information from O*Net and construct an industry-level index *Exposure*, which defines how many jobs could not be done at home during the lockdown. This index, meanwhile, shows the industrial exposure to the pandemic.

Finnish companies maintain the widest presence in the dataset, the amount of borrowing is considered less substantial relative to alternative economies.[6] Regarding sectoral distribution, the sectors with the largest number of companies are Industrial (26.14%), Consumer Discretionary (14.32%), Materials (13.98%), Technology (10.61%), and Communications (8.89%). The dataset includes ten BICS sectors in total. Figure 6 illustrates the credit line drawdowns across sectors. The upper two plots in the figure show that the Industrial sector has the most quantity of the drawdowns, while the drawdowns account for the biggest part of the balance sheet in the Energy sector. The lower two plots show that the Energy sector has the greatest increase in drawdowns in terms of the quantity and the size related to the assets. In contrast, energy, technology and materials have marginally increased their drawdown-to-total assets ratios during 2020:Q2 relative to the previous quarter. There is indeed a significant heterogeneity in which firms drew down credit lines.

The study collects (country-level) quarterly data on the COVID-19 confirmed cases per million from the European Centre for Disease Prevention and Control (ECDC). Meanwhile, we obtain data on social distancing strictness across European countries from Our World in Data, following Ritchie et al. (2020)'s research in the Oxford Stringency Index. Following the literature (For example, Campello et al. (2011), Acharya et al. (2012, 2020)), we use companies characteristics that may affect utilization of revolving credit facilities during the 2020:Q2 shock: cash holdings, leverage, company size (measured by the logarithm of total assets), tangible assets, undrawn credit lines, and price-to-book ratio. Cash holding forms an essential consideration, along with corporate credit line usage. Companies with steady internal liquidity resources maintain their repayment abilities, enabling them to access external funds such as revolving credit facilities.

We also consider leverage, which can have a consequential impact on credit lines. Early theoretical papers highlighted their roles in understanding credit line drawdowns (namely, Martin & Santomero (1997), Holmström & Tirole (1998)). Company size and tangible assets are also important in corporate credit lines (see amongst the others Chodorow-Reich et al. (2022), Nikolov et al. (2019)). Finally, undrawn credit lines provide potential drawn amounts for the next period. The price-to-book ratio (P/B) is a valuation tool to assess whether a company's stock price is overvalued or undervalued relative to its book value per share. It reflects the company's financial performance in the secondary market. We further examine the financial constraints and credit line drawdowns, where we use a proxy

[6] The countries with the largest drawdown sizes are Germany with €60.22bn (32.57%), France with €41.98bn (22.71%), Spain with €35.43bn (19.17%), Italy with €19.17bn (10.37%), and Portugal with €8.64bn (4.67%) in our sample. Finland, for example, with €6.80bn only accounts for 3.68%.

for liquidity distress, following Bosshardt & Kakhbod (2020) 's approach. We use the earnings before interest, taxes, depreciation, and amortization (EBITDA) to measure a company's cash flow.[7] Table (1) shows the summary statistics where all variables are normalized by total assets. The average (median) credit line drawdowns is 4.5% (0%).[8] The average (median) credit line usage is 20.7% (0%). Revolving credit lines are facilities commonly used by banks to supply cash to companies. The average (median) company has a cash flow of 2.5%. As for financial characteristics, the average (median) company has a cash holding of 8.9% (7%), capital expenditure of 1.1% (1.5%), the leverage ratio of 30.2% (28.3%), the logarithm of total assets of 21.52 % (21.64%), the tangible assets of 75.3% (80.9%), undrawn credit line of 10.6% (8.4%), and the logarithm of price-to-book ratio of 0.53 (0.52). Alternatively, we include free cash flow to study the revenue shortfall, with an average (median) value of 1.6% (1.4%).

Company exposure to the pandemic varies, with an average (median) 65.8% (78%) of jobs adversely affected when done at home in 2020. In terms of the country-level data, the average number of COVID-19 confirmed cases was around 1,654 per million. Table (2) documents the cases across countries in our sample, with 63.7% of companies highly exposed within countries with relatively high infection rates. The average (median) of companies were located in countries with moderate strictness of lockdown policy, around 50.9 with reference to Ritchie et al. (2020), where the index of 100 indicates the strictest lockdown policy, while the score zero represents the absence of social distancing.

Figure (7) shows the weighted credit line drawdowns and credit line drawdown size for all Euro-area companies in the sample. In the left panel, we scale drawdowns by the number of companies within each quarter. European companies drew down credit lines at the start of the pandemic. In Figure (8A), we note a significant increase in cash holdings during the same period. This figure also shows the trend in liquidity accumulation before and after the pandemic period. Specifically, average cash holdings, including cash and cash-equivalent components, scaled by the total assets, increased sharply during the pandemic. The sharp increase in cash holdings is consistent with Anderson & Carverhill (2012) and Bolton et al. (2011) and suggests an increase in liquid assets to mitigate the impact of possible liquidity shocks. These statistics demonstrate that the EU companies withdrew from their credit lines in anticipation of a possible liquidity shock. According to the existing studies, credit line drawdowns

[7] This definition follows the same approach adopted in the literature (Sufi 2009, Acharya & Steffen 2020, Greenwald et al. 2021, Brown et al. 2021).

[8] The skewness of drawdown size widely exists. Literature like Brown et al. (2021) shows the same skewness as ours (all zeros from 0% to 75% percentiles).

may also be associated with investments. In Figure (8B), we use capital expenditure as a proxy for investment. There is limited evidence that EU companies used credit lines to support investments during the pandemic. Acharya & Steffen (2020) and Bosshardt & Kakhbod (2020) provide empirical evidence for the United States and show that the "dash for cash" of the US companies during the pandemic period was mainly driven by precautionary saving reasons. However, the studies provide limited insights into companies' investments during the COVID-19 period. In the Online Appendix, we confirm these findings using a panel regression and capital expenditure as a dependent variable. We do not find evidence that companies used credit lines to support investments in 2020:Q2.

Corporate credit lines and the overall importance of banking institutions in providing short-term liquidity to companies are more prominent within Europe, relative to the US economy, where money market instruments such as commercial papers and repurchase agreements are considered prevalent. Nonetheless, the empirical evidence suggests that companies rely on credit lines for three distinct purposes. In this paper, we argue that corporate credit line drawdowns are related to both the short-term and long-term financial drivers, including the balance sheet, income and cash flow statement. More specifically, the short-term drivers encompass earning realizations, current assets and current liabilities. These form the primary indicators considered by companies when deciding on corporate credit line drawdowns. However, companies with a steady position on long-term assets such as PPE, whilst also holding low long-term obligations, exhibit higher reliance on corporate credit lines when experiencing significant shortfalls in their short-term earnings (for example, Real Estate and Material industrial sector). This reliance on credit lines declines as long-term obligations increase.

[Figure (1) here]

We argue that companies' reliance on transitory earning shortfalls is explained by the pressing motives to meet current obligations such as maturing financial contracts and wages. More specifically, we observe an association between unexpected earning shortfall realizations and an ex-post reliance on credit line drawdowns. Furthermore, we argue that companies with limited long-term assets and high long-term obligations, which concurrently have short-term liquidity constraints, are considered financially constrained and may lack access to corporate credit lines. We observe that such constraints appear either in the form of unavailable credit line capacity or due to increasing costs associated with credit lines, given both unsteady long-term and short-term financial outcomes. An alternative strand of the literature sheds light on the associations between credit lines and investment motives. We observe that credit lines are less frequently relied on for investment purposes. However, there is empirical evidence associating companies with steady earning outcomes with the credit lines used for investment purposes. This observation may arise across companies with high net long-term assets and otherwise for those with high long-term obligations, such as younger companies with low PPE (software or technology) whilst generating high growth and steady short-term earnings.

3 Earning Drivers of Credit Line Drawdowns

We provide empirical evidence that companies' reliance on credit lines spikes when earnings fall below a specific threshold. While this finding is consistent with the existing literature pointing to the precautionary role of credit lines, it also provides a novel causal identification of the financial conditions that lead to credit line drawdowns.

We conjecture that liquidity provision via credit lines and a company's earnings are endogenously driven. For example, earning shortfalls limit financial resources, which subsequently trigger the company to rely more actively on alternative (external) financing channels. However, the liquidity provisions via credit lines may reversely drive earnings outcomes. This simultaneity between the earnings and credit line drawdowns leads to a statistical selection, where the relationship between the earnings and financing decisions may be empirically mis-specified. For example, companies with steady positive earnings exhibit lower reliance on external financing, whereas those with negative earnings are expected to rely more actively on external financing channels (credit lines), which, subsequently, may feed into the earnings. In this study, to address this issue, we propose a regression discontinuity design (RDD) to uncover the underlying relationship between the earning outcomes and the credit line drawdowns.

Company earnings may vary due to internal and external drivers. In our framework, we focus on a narrow interval of earnings realizations around the zero-earnings outcomes. This set-up assumes that companies considered within the narrow interval share more common characteristics. In other words, their earnings throughout the sample size remain similar, with narrow variations around the zero outcome. Given that the set-up focuses on a narrow interval, observing significant changes in the drawdown decisions is attributed to the zero-threshold outcomes. From an economic perspective, the RDD design assumes that companies considered within the interval are comparable across several dimensions, including overall internal operations.

[Figure (2) here]

The earning outcome is determined according to a bandwidth parameter λ to limit the observations to those companies within a narrow neighbourhood of the break-even (zero) earning outcome. More specifically, let D_i equal to one when earning outcomes are in the interval $[0, \lambda)$, and equal to zero for companies with marginally negative earnings in $(-\lambda, 0)$. The framework tests the null hypothesis that drawdown decisions and earning outcomes are expected to exhibit a continuous relationship throughout the realizations within the narrow neighbourhood around zero earnings. Alternatively, significant discontinuous variations suggest that the reliance on credit line drawdowns is triggered by earnings. Formally, we test the following specification:

$$\text{Drawdown}_{i,t} = \beta_0 + \beta_1 D_{i,t}(\lambda) + \beta_2 D_{i,t}(\lambda) \times 2020\text{:Q2} + \gamma X_{i,t} + \epsilon_{i,t} \tag{1}$$

This specification considers a before-and-after 2020:Q2 set-up to examine the drawdown decision responses following a shock which impacts the company earnings. $\text{Drawdown}_{i,t}$ is a ratio with respect the total assets and 2020:Q2 is a dummy indicating the pandemic period. The specification includes a set of controls $X_{i,t}$ containing cash holding, financial constraints, the undrawn amount of credit lines, tangible assets scaled by total assets, the natural logarithm of total assets, the price-to-book ratio, and the leverage ratio.[9]

The choice of the bandwidth serves an important function in driving the results. In particular, tighter choices of the bandwidth reinforce the causality of earnings affecting drawdowns while reducing the sample size available for the estimation. Conversely, as the bandwidth widens, earning outcomes are permitted to differ, hence lowering the causal evidence and increasing the sample size available for estimation. Hoxby (2000), Chava & Roberts (2008), and Imbens & Wager (2019) provide an in-depth investigation of the bandwidth selection with the aim of proposing a unique bandwidth selection that optimally chooses the two attributes discussed earlier. Chang et al. (2014), Chemmanur & Tian (2018), and Bernile et al. (2023) use a regression discontinuity design within empirical corporate finance to establish causal relationships based on abrupt exogenous variations within a narrow interval of the outcomes of interest where the choice of bandwidth is determined either optimally or heuristically. In this study, we establish robustness by considering a wide range of bandwidths to present empirical results across several bandwidth selection scenarios.

[9] Time and industry fixed effects are included.

The baseline empirical design is implemented to ensure that companies with at least one (or more) observation before and after 2020:Q2 are selected. Figure (2) provides an illustrative representation of the hypothesized relationship between earning outcomes and drawdown decisions. The illustrative representative assumes that marginal earning outcome variations near the zero threshold (horizontal axis) arise beyond companies' control, while companies positioned just above or below this threshold are expected to share similar internal financial and operational characteristics affecting both financing decisions and earning outcomes. The alternative curve presents a contrasting continuous relationship between the relevant variables. The vertical axis is not necessarily centred at zero, and the horizontal axis measurements represent the bandwidth choice corresponding to the standard deviation of the earning to total assets ratio (σ). The empirical results associated with the RDD framework presented in Table (3) suggest that, first, with the bandwidth choice $\lambda = \pm 0.25\sigma$, credit line drawdown-to-total assets increase by 3.173 percentage points, when companies earning-to-total assets decline unexpectedly by one percentage point ($\lambda = -0.25\sigma$). While this increase in the drawdown is statistically significant, the counterpart estimation results show no empirical relationship between the credit drawdowns and marginally positive earning outcomes ($\lambda = +0.25\sigma$). The subsequent results across all identically distanced additional bandwidth selections provide consistent results and evidence that the ratio of drawdown-to-total assets increases significantly (at least at 95% and occasionally at 99% levels) between $(2.343, 3.173)$ percentage points given a one percentage point decline in the earning-to-total assets ratio, whilst also maintaining an insignificant relationship across the positive earning outcomes.

[Table (3) here]

The results discussed above provide evidence in support of reliance on credit line drawdowns when facing earning shortfalls, whilst no evidence in support of drawdowns when realizing positive earning outcomes. We further investigate the empirical findings suggested by Equation (1) and consider joint estimations (and inference) associated with the differential effects of drawdown decisions simultaneously between the positive versus the negative earning outcomes. While the results map to the identical sum of the estimated results previously reported, the statistical inference embeds further insights, particularly by incorporating additional covariations between the two previous estimated results to provide an extended robustness analysis. Figure (4) shows the estimated cross-sectional differential percentage point changes in the drawdown to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in drawdown decisions across the pairwise above- versus below-threshold value. The horizontal axis shows several bandwidth selections proportional to the standard deviation of the empirical distribution summarizing EBITDA observations. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections consider even intervals around zero earnings and show a sharp shift in the companies' behaviours to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.

4 Labour Frictions and Supply-side Constraints

We focus on the supply-side component of earnings with an impact on credit line drawdowns. We conjecture that the 2020:Q2 shock negatively impacted labour and, as a (causal) consequence, the earning outcomes of the companies with a variable heterogeneity according to the labour-driven exposure.

From an empirical perspective, however, earning outcomes and external financing decisions, namely credit line drawdowns, are assumed to be endogenously determined together with labour market allocations. For example, positive earnings enable companies to expand labour, which, accordingly, supports earnings. Our framework exploits the inelastic nature of labour during the 2020:Q2 aggregate shock to address the empirical identification problem, where disruptions in the labour supply following the 2020:Q2 shock limit companies' output capacities and subsequently lower their operating turnovers. Therefore, we propose a two-stage least squares (2SLS) approach, where we first establish exogenous variations in labour as a driver of earnings to subsequently explain credit line drawdowns. We employ a survey developed by Dingel & Neiman (2020) and conducted on a wide range of 1,000 occupations in the United States that characterizes labour productivity when distanced from a conventional on-site work setting. Social distancing and flexible working arrangements, amongst other drivers, impacted labour productivity. While social distancing and flexible working arrangements were introduced and adapted to the aftermath of the 2020:Q2, the unprecedented nature of the shock adversely and unexpectedly impacted the earnings and financial decisions. The framework in this study defines exposure to labour capacity to maintain productivity following the 2020:Q2 shock as an important measurement to distinguish between companies adversely affected by the shock versus those that maintained productivity regardless of the shock to their labour inputs. More specifically, we use a two-digit sector classification code to identify companies' exposure across industries.

Let $\alpha \in [0,1]$ denote the metric proposed by Dingel & Neiman (2020) across the classification developed in this study, which measures the capacity to work away from an on-site work setting where 1.0 corresponds to maintaining perfect productivity, and zero corresponds to the loss of entire productivity when away and define:

$$Exposure = 1 - \alpha$$

In this context, the least impacted industries are documented to be professionals, scientific, and technical services with an impact factor of $\alpha = 0.8$, indicating that most occupations under these classifications remained relatively less affected by the emergence of the shock, whereas the accommodation and food services are documented to be most affected ($\alpha = 0.04$). Thus, a higher exposure value implies a lower ability of occupational capacities to be fulfilled while impacted by the pandemic. While the framework developed by Dingel & Neiman (2020) uses the North American Industry Classification System (NAICS), in this study, we follow the Bloomberg Industry Classification Standard (BICS). These two systems overlap in certain occupational types with specific disparities. For example, sectors are divided into unequal divisions,[10] and the definition of level-2 sub-sector remains generic. We develop a detailed matching across the two systems by exploiting the classification information provided by each benchmark at level-3 industry groups and level-4 industries. Table (5) shows the industrial exposure to COVID-19 within two industrial levels. Figure (9) shows companies' access to their credit lines between 2020:Q1 and 2020:Q2, where Energy, Technology, Real Estate and Materials are among the leading sectors that withdrew their credit lines during the pandemic shock. The baseline 2SLS framework is as follows,

$$\text{First Stage: } EBITDA_{i,t} = \delta_0 + \delta_1 . \mathbb{I}(Exposure) + \eta_{i,t} \tag{2}$$

$$\begin{aligned} \text{Second Stage: } Drawdown_{i,t} &= \psi_0 + \psi_1 \widehat{EBITDA}_{i,t} + \psi_2 \widehat{EBITDA}_{i,t} \times \mathit{2020{:}Q2} \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where the $\mathbb{I}(Exposure)$ classifies the company exposure to exposed and non-exposed, according to the

[10] The number of level-1 or 2-digit sectors in the NAICS is 20, while the number in the BICS is just 13.

exposure values above 0.75 and below 0.3, respectively:

$$\mathbb{I}(Exposure) \quad = \quad \begin{cases} 1 & \text{if } Exposure \geq 0.75 \\ 0 & \text{if } Exposure \leq 0.3 \end{cases}. \tag{4}$$

Table C1 in Appendix C shows the results of the first stage in Equation (2), while Table 4 shows the results of the second stage in Equation (3). Our empirical results provide evidence consistent with the findings reported in the previous sections. These results further draw on two notable aspects. First, by focusing on labour, we study an important component of earnings, which can drive credit lines' drawdowns. Table (4) Column (5) reveals that companies, in response to a one percentage point decline in the predicted decline in the earning-to-total assets ratio, increase their reliance on credit line drawdown-to-total assets by an average of 0.74 percentage points. Furthermore, these findings are consistent with the evidence established in earlier sections. The previous section showed that companies' reliance on credit line drawdown increases when earnings fall into the negative region. The findings in Table (4), Columns (2)-(3) shed further light on this issue, suggesting that the company's reliance on credit lines increases in response to earning shortfalls by 1.66 percentage points, whereas there is no empirical finding to support a statistically significant reliance on the credit line drawdowns when earnings are positive.

The empirical results in Table (4) suggest a negative relationship between cash flow and total credit line size at the peak of the shock in 2020:Q2. These results are robust across the specifications provided, suggesting that credit institutions maintained the supply of liquidity on average to companies at the peak of the 2020:Q2 shock and provided them with the necessary credit insurance.

[Figure (3) here]

[Table (4) here]

The impact of the 2020:Q2 shock is different from the weather shock examined in Brown et al. (2021), as the latter is exogenous to company operations. At the same time, the 2020:Q2 shock is exogenous but only partly idiosyncratic since it is related to the degree of company's labour work flexibility. The results in this section explain how different companies across countries and industries manage their short-term liquidity risk when hit by an exogenous shock. An interesting and novel aspect of our results is that banks accommodated the demand for liquidity insurance following this shock, while they did not do so during the 2008 financial crisis.

5 Financial Constraints

The causal identification in previous sections shows that credit lines provide an essential source of liquidity to mitigate short-term earning shortfalls. Nevertheless, companies' financing decisions are simultaneously driven by alternative key financials and company fundamentals. The current assets and current liabilities are considered within the close vicinity of the credit lines in terms of providing alternative short-term resources or, conversely, deepening current liquidity requirements. While this premise provides a more comprehensive approach, it also makes a distinction between types of companies: the one with steady financial standings, defined in this context on the basis of overall steady earnings and high liquidity ratio, versus those with unfavourable earning outcomes and low liquidity ratio. We define the latter type as financially constrained companies. Sufi (2009) shows that financially constrained companies generally rely on higher cash holdings to manage liquidity shocks.[11] This observation is consistent with the data in this study, suggesting that the cash holding account serves as a fallback alternative when external financing channels become limited or expensive in response to the company's financial type. Campello et al. (2011) provide empirical evidence that during the financial crisis period, companies substitute cash holding with credit lines in the presence of liquidity shocks. Acharya & Steffen (2020) show that US companies raise cash to offset changes in credit risk following the 2020:Q2 shock. Conversely, Ivashina & Scharfstein (2010), Bosshardt & Kakhbod (2020) and Berrospidea & Meisenzahlb (2022) show that companies' credit line drawdown variations are explained by companies' incentives to mitigate liquidity shocks and providing precautionary resources in anticipation of impending shocks.

We incorporate the measure of financial distress developed in Bosshardt & Kakhbod (2020) to combine the net income, cash and cash equivalent, and short-term debt, scaled by the total assets, to further investigate credit line drawdowns in response to a wider set of company financials:

$$\text{Distress}_t = \frac{\text{Short-term Debt}_t - \text{Cash \& Cash Equivalent}_t - \text{Net Income}_t}{\text{Total Assets}_t} \tag{5}$$

where higher (lower) Distress_t implies a tighter (looser) liquidity-based financial constraint reflecting

[11] Sufi (2009) shows that less financially constrained companies, on average, rely on credit lines while financially constrained companies use cash to manage liquidity shocks. However, this finding focuses on the period before the 2008 financial crisis when credit was abundant and primarily to satisfy covenants.

a more limited capacity to meet current liabilities. This composite ratio provides a consistent continuation to focus on earning outcomes whilst also considering the gap between the short-term debt and cash holdings to enable the study to incorporate an extended set of financial drivers. Given the wider basis of the analysis, an empirical identification to establish the causal relationship between the composite ratio and any outcome of interest, similar to the methodological approaches in the Sections (3)-(4), is challenging. This, in particular, is because the composite ratio spans balance sheet and income statement items, further limiting the scope to establish a common exogenous driver. Nevertheless, the 2020:Q2 aggregate shock that impacted company financials provides a plausible setting to investigate credit drawdown responses to wider financial indicators following the specification below:

$$Drawdown_{i,t} = \theta_0 + \theta_1 Distress_{i,t} + \theta_2 Distress_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{6}$$

where the notations and controls are defined earlier. We test the association between the distress ratio and credit line drawdowns using the whole sample and by conditioning on dummies that account for the pandemic shock in 2020:Q1, 2020:Q2 and 2020:Q3. Firstly, we note that only the intersection dummy in 2020:Q2 is statistically significant, as expressed in Table (7), Panel (B). Secondly, we note a significant positive association between companies' distress (cash holding) and credit line drawdowns, similarly demonstrated in the same panel and the whole sample. Campello et al. (2011), for the financial crisis period and US companies, show a negative relationship between credit line drawdowns and cash holdings and interpret it as a substitution effect between internal and external liquidity. We do not find this for European companies during the 2020:Q2 shock. We interpret the negative relationship between the distress factor and credit line drawdowns as suggesting that companies with less stringent financial constraints used credit lines during the 2020:Q2 shock. Companies with less stringent financial constraints drew down their credit lines and topped up cash holdings in 2020:Q2, while there is insignificant evidence that this also continued after 2020:Q2.

[Figure (5) here]

Figure (5) shows the relationship between the composite distress ratio and cash holding balances. We note that in the pre-2020:Q2 period, only financially constrained companies held higher cash provisions, but this changed in the post-2020:Q2 period when financially constrained and unconstrained companies held higher liquidity provisions.

[Table (6) here]

In Figure (10), we show the change in cash holding in 2020:Q2 and the distress ratio. Companies with the most remarkable change in cash holding were the ones within the Low Distress group. These results suggest that during the pandemic shock, companies with less stringent liquidity constraints drew down credit lines and increased cash holdings. In the next section, we shall try to understand why. Firstly, we do not find a substitution effect as in Campello et al. (2011) for European companies during the pandemic shock. Instead, our results suggest that in 2020:Q2, a panic borrowing occurred amongst European companies, leading to the observed fly to liquidity. These are new results, which we will investigate further in the following sections.

6 Conclusion

Corporate credit lines have remained an indispensable source of short-term liquidity management, particularly across the European financial systems where bank-based financial intermediation serves a significant role. We provide novel empirical evidence that in the first quarter of 2022, the outstanding funds acquired via the credit lines by European companies reached €87bn, accounting for 5.15% of their total assets in 2020:Q2. Our study first provides a causal identification to quantify corporate credit line drawdown decisions as a response to unexpected shortfalls in the realized earnings, where, in particular, we show that drawdowns increase by an average of 3.173 percentage points, measured in terms of credit line drawdowns scaled by the total assets, in response to a one percentage point (unanticipated) decline in the corporate earnings to their total assets. While this result provides causal evidence, it remains focused on the discontinuity defined at the zero-earning threshold. We further investigate the comprising components of company earning outcomes and argue that the inelastic nature of labour in generating corporate earnings during the 2020:Q2 provides an alternative identification framework to trace exogenous shocks to the labour initially towards earning outcomes and subsequently measure the corresponding variations on the drawdown decisions. The results remain consistent with the findings established via the RDD framework, where the quantity of reliance on corporate credit lines is shown to be 1.67 percentage points given a unit change in the earning realizations for the companies with higher exposures to labour shocks while consistently establishing no credit drawdown result for companies with lower exposures to the shock. At the industry level, we showed that firms with less work flexibility drew down their credit lines, and banks accommodated the demand, when the net long-tern asset warranted the credit extension.

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Manuscript Figures and Tables

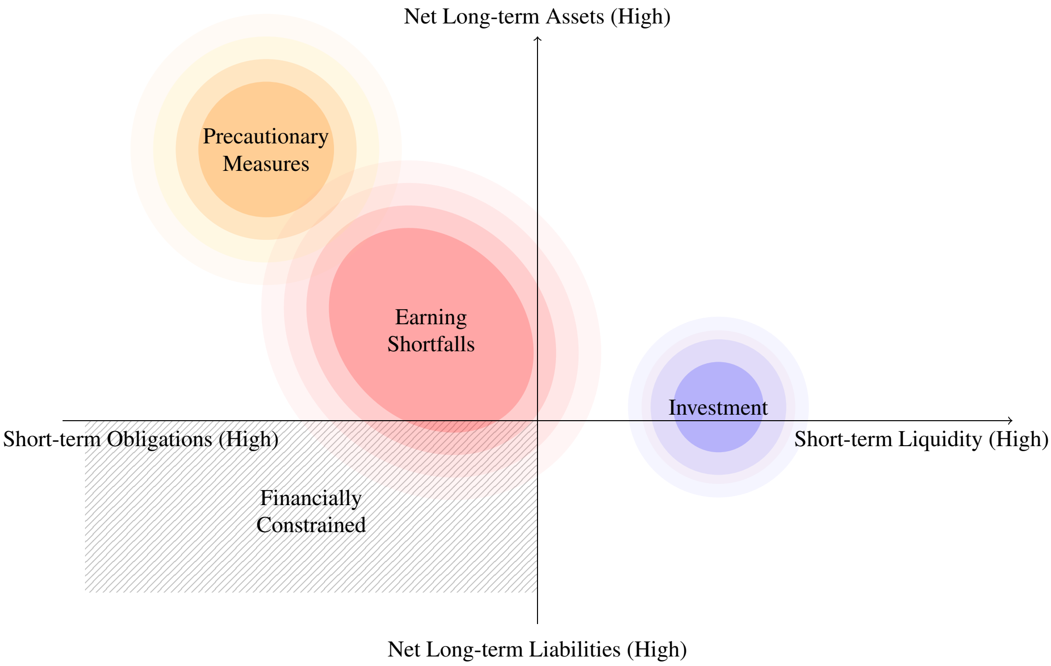

Figure 1. The diagram depicts short-term liquidity drivers (specifically characterized as the difference between short-term debt − cash holding − net income) on the horizontal axis versus long-term assets minus long-term liabilities on the vertical axis. The intensity of each shaded region determines credit line drawdowns over three regions. Companies with marginally negative short-term liquidity with steady long-term assets rely on drawdowns to mitigate transitory earning shortfalls whereas companies with more tangible assets such as PPE less the long-term obligations rely on credit line drawdowns for anticipatory motives and precaution against potential liquidity shortfalls. Companies with steady and positive short term liquidity resources on less frequent cases rely on credit line drawdowns for investment motives which may be associated with positive or negative net long-term assets. Financial standings concurrently involving liquidity shortages on short-term together with the high long-term obligations and low long-term assets are considered to be financial constrained.

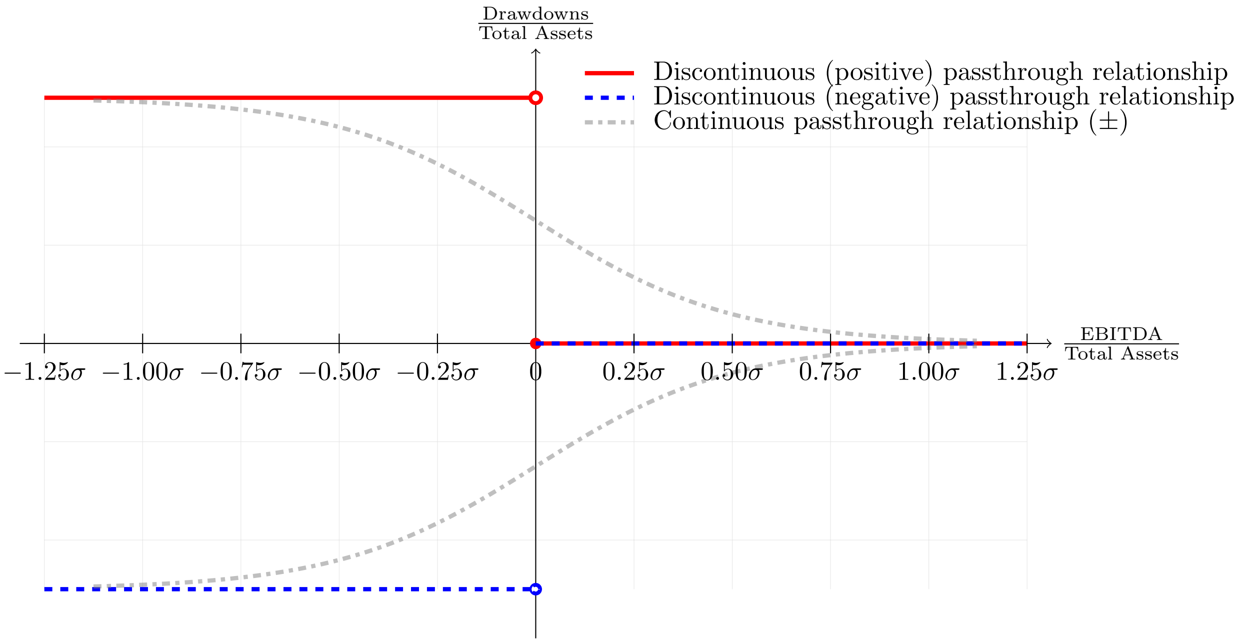

Figure 2. The diagram depicts an illustrative representation of the relationship between the earning outcomes and drawdown decisions. Earning outcomes in narrow neighborhoods around the zero-earning outcome (horizontal axis) are assumed to be realized beyond companies' control, whereas companies selected just above or just below the zero threshold are expected to share common internal financial and operational characteristics between the financing decisions and earning outcomes. A discontinuous response of the drawdowns around the zero-earning outcome is hypothesized to arise due to companies' limited internal earning resources and reliance on external financing. The alternative curve is illustrative as a contrasting continuous relationship between the variables of interest. The vertical axis is not necessarily centered at zero. The measurements across the horizontal axis denote the choice of bandwidth corresponding to the standard deviation of the variable associated with the axis.

	Obs.	Mean	Std. Dev.	Min	0.25	Median	0.75	Max
Firm-level variables								
Drawdown Size	842	0.045	0.096	0.000	0.000	0.000	0.037	0.638
Credit Line Usage	844	0.207	0.297	0.000	0.000	0.000	0.387	1.000
EBITDA	1,055	0.025	0.027	−0.359	0.015	0.025	0.036	0.175
Cash Holding	1,157	0.089	0.073	0.000	0.039	0.070	0.124	0.661
Capital Expenditure	969	0.011	0.011	0.000	0.004	0.008	0.015	0.174
Leverage	1,157	0.302	0.169	0.000	0.190	0.283	0.403	1.203
Log(Assets)	1,157	21.517	2.050	15.644	20.017	21.644	22.868	26.914
Tangible Assets	1,144	0.753	0.218	0.001	0.611	0.809	0.941	1.000
Undrawn Credit Line	1,133	0.106	0.097	0.000	0.042	0.084	0.136	0.873
Log(P/B)	1,130	0.532	0.834	−4.275	0.061	0.520	1.010	7.343
RID	542	0.309	0.367	−2.716	0.185	0.380	0.524	0.881
Distress	1,119	−0.025	0.155	−3.459	−0.080	−0.019	0.040	0.651
Free Cash Flow	966	0.016	0.043	−0.524	−0.002	0.014	0.033	0.354
Exposure	1,159	0.658	0.205	0.200	0.580	0.780	0.780	0.860
I(Exposure)	960	0.780	0.414	0.000	1.000	1.000	1.000	1.000
Country-level variables								
High COVID Exposure	234	0.637	0.482	0.000	0.000	1.000	1.000	1.000
Log(Stringency)	312	3.930	0.338	3.324	3.561	3.948	4.267	4.498
Log(Cases)	312	7.411	0.988	5.358	6.913	7.523	8.151	9.693

Table 1. **Summary Statistics** (Full sample).

Country	2020Q1	2020Q2	2020Q3
Austria	1,038.323	1,975.884	4,957.475
Belgium	1,100.21	5,290.223	10,201.336
Estonia	560.698	1,496.951	2,537.064
Finland	302.024	1,311.237	1,849.533
France	774.658	3,028.092	8,958.471
Germany	742.286	2,329.006	3,467.498
Greece	110.671	326.365	1,768.727
Italy	1,785.81	4,061.051	5,314.977
Latvia	212.389	596.611	973.361
Luxembourg	3,406.739	6,724.322	13,309.433
Malta	320.837	1,271.955	5,805.433
Netherlands	778.21	2,880.407	7,128.681
Portugal	723.316	4,095.294	7,341.229
Slovenia	378.407	754.927	2,684.709
Spain	2,019.987	5,249.254	16,197.887

Table 2. COVID Confirmed Cases per Million.

Dependent Variable: Drawdown-to-Total Assets										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	-0.25σ	0.25σ	-0.5σ	0.5σ	-0.75σ	0.75σ	-σ	σ	-1.25σ	1.25σ
EBITDA$_t$	0.146	-1.071**	-0.112	-1.002***	-0.326	-0.869***	-0.257	-0.784***	-0.194	-0.722***
	(0.410)	(0.510)	(0.386)	(0.368)	(0.401)	(0.291)	(0.354)	(0.256)	(0.344)	(0.253)
EBITDA$_t \times$2020:Q2	-3.173***	0.873	-2.778***	0.430	-2.316**	-0.398	-2.343**	-1.293	-2.507**	-1.305
	(1.005)	(3.851)	(0.975)	(1.236)	(1.000)	(1.008)	(0.974)	(0.909)	(0.967)	(0.928)
log(Assets$_t$)	0.000	-0.012**	-0.005	-0.009**	-0.005	-0.012***	-0.005	-0.008***	-0.005	-0.009***
	(0.007)	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
Leverage$_t$	0.085	0.090	0.125*	0.078*	0.135**	0.077**	0.145**	0.068**	0.111*	0.064**
	(0.067)	(0.060)	(0.065)	(0.040)	(0.063)	(0.032)	(0.061)	(0.028)	(0.059)	(0.028)
Undrawn CL$_t$	0.337***	0.425***	0.312***	0.352***	0.287***	0.263***	0.284***	0.283***	0.271***	0.243***
	(0.098)	(0.091)	(0.089)	(0.066)	(0.091)	(0.052)	(0.090)	(0.046)	(0.088)	(0.042)
log(Price$_t$)	0.003	0.007	0.005	0.009	0.000	0.004	0.001	0.001	0.002	0.003
	(0.012)	(0.009)	(0.010)	(0.006)	(0.009)	(0.005)	(0.009)	(0.004)	(0.008)	(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85	110	115	213	149	309	157	387	169	427
Adjusted R^2	0.237	0.267	0.253	0.208	0.150	0.153	0.148	0.148	0.121	0.133

Table 3. **Regression Discontinuity Design and Credit Lines Drawdowns** — This table shows credit line drawdowns on revenue within various groups based on cash flow. The dependent variable is *Drawdown Size*, credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included. Columns (1), (3), (5), (7), and (9) use sub-samples based on the performance just below the threshold. The rest of the columns use sub-samples based on the performance just above the threshold. σ denotes the standard deviation of the performance. A real number multiplying σ (for example, -0.5σ) represents the direction and distance away from the threshold. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Drawdown-to-Total Assets				
	(1)	(2)	(3)	(5)	(4)
	All	Exposed Firms	Unexposed Firms	All	3-Way Interaction
$\text{EBITDA}_{i,t}$	-0.186	-0.091	-0.390	-2.418***	-0.532
	(0.138)	(0.155)	(0.406)	(0.689)	(0.359)
$\text{EBITDA}_{i,t}\times$2020Q2	-1.212**	-1.666***	-0.200	-0.740*	0.266
	(0.510)	(0.602)	(0.869)	(0.436)	(0.729)
$\text{I}(\text{Exposure}_i)$					0.028
					(0.018)
$\text{EBITDA}_{i,t}\times\text{I}(\text{Exposure}_i)$					0.450
					(0.377)
$\text{I}(\text{Exposure}_i)\times$2020:Q2					0.027*
					(0.016)
$\text{I}(\text{Exposure}_i)\times\text{EBITDA}_{i,t}\times$2020:Q2					-1.968**
					(0.927)
$\text{Leverage}_{i,t}$	0.083***	0.108***	0.079**	0.037	0.086***
	(0.024)	(0.031)	(0.034)	(0.024)	(0.024)
$\log(\text{Assets}_{i,t})$	-0.005***	-0.003	-0.019***	-0.006***	-0.005***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Undrawn $\text{CL}_{i,t}$	0.366***	0.417***	0.245***	0.367***	0.371***
	(0.035)	(0.043)	(0.051)	(0.033)	(0.035)
$\log(\text{P/B}_{i,t})$	-0.007	-0.002	-0.008	0.025**	-0.004
	(0.005)	(0.006)	(0.008)	(0.010)	(0.005)
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	663	527	136	698	663
Adjusted R^2	0.189	0.201	0.234	0.179	0.198

Table 4. **Credit Lines Drawdowns and EBITDA during the 2020:Q2 crisis (OLS & 2SLS).** This table shows the results from Equation (3) in OLS and 2SLS forms. The dependent variable is credit line drawdowns scaled by total assets. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the second quarter of 2020, and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix A. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Level-1 BICS Sectors			
Sector	Exposure	Sector	Exposure
Materials	0.772	Consumer Staples	0.685
Health Care	0.771	Industrials	0.651
Consumer Discretionary	0.720	Utilities	0.630
Energy	0.710	Real Estate	0.580
Technology	0.697	Communications	0.272

Panel B: Level-3 BICS Industry Groups			
Industry	Exposure	Industry	Exposure
Retail-Consumer Staples	0.86	Tobacco & Cannabis	0.78
Retail-Discretionary	0.86	Health Care Facilities & Services	0.75
E-Commerce Discretionary	0.86	Oil & Gas Services & Equipment	0.75
Engineering & Construction	0.81	Oil & Gas Producers	0.75
Transportation & Logistics	0.81	Construction Materials	0.75
Home Construction	0.81	Metals & Mining	0.75
Software	0.78	Leisure Facilities & Services	0.7
Transportation Equipment	0.78	Gas & Water Utilities	0.63
Machinery	0.78	Electric Utilities	0.63
Aerospace & Defense	0.78	Renewable Energy	0.63
Chemicals	0.78	Electricity & Gas Marketing & Trading	0.63
Electrical Equipment	0.78	Real Estate Owners & Developers	0.58
Beverages	0.78	REIT	0.58
Technology Hardware	0.78	Real Estate Services	0.58
Steel	0.78	Food	0.48
Medical Equipment & Devices	0.78	Wholesale-Discretionary	0.48
Containers & Packaging	0.78	Wholesale-Consumer Staples	0.48
Apparel & Textile Products	0.78	Publishing & Broadcasting	0.28
Biotech & Pharma	0.78	Cable & Satellite	0.28
Industrial Intermediate Products	0.78	Internet Media & Services	0.28
Diversified Industrials	0.78	Technology Services	0.28
Home & Office Products	0.78	Telecommunications	0.28
Forestry, Paper & Wood Products	0.78	Entertainment Content	0.28
Semiconductors	0.78	Industrial Support Services	0.2
Automotive	0.78	Commercial Support Services	0.2
Household Products	0.78	Advertising & Marketing	0.2
Leisure Products	0.78	Consumer Services	0.2
Construction Materials	0.78		

Table 5. **Industrial Exposure to the COVID-19 Shock**. This table shows the pandemic exposure across industries. The upper panel displays the exposure across Level-1 BICS sectors. The lower panel displays the exposure across Level-3 BISC industry groups.

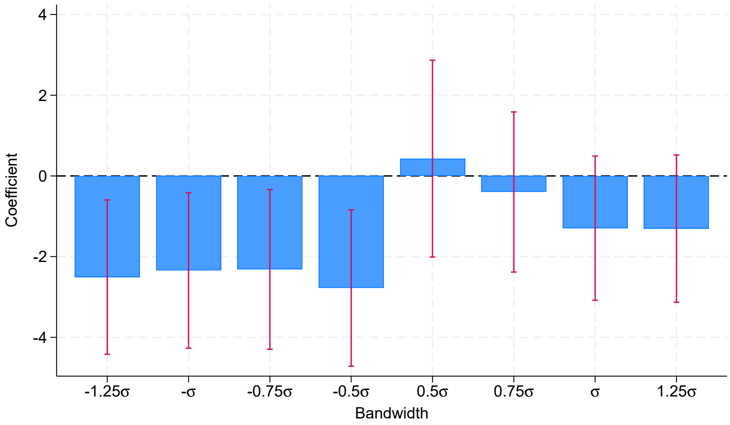

Figure 3. The diagram shows the estimated percentage point changes in the drawdown to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. The horizontal axis shows several bandwidth selections. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections consider even intervals around zero-earning outcomes and show a sharp shift in the firms' behaviors to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.

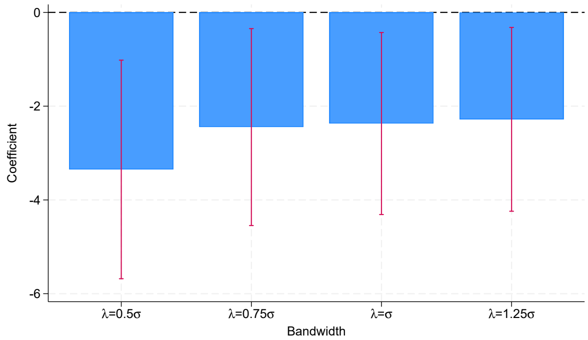

Figure 4. The diagram shows the estimated cross-sectional differential percentage point changes in the drawdown to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in drawdown decisions across the pairwise above- versus below-threshold value. The horizontal axis shows several bandwidth selections proportional to the standard deviation of the empirical distribution summarizing EBITDA observations. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections consider even intervals around zero-earnings and shows a sharp shift in the firms' behaviors to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.

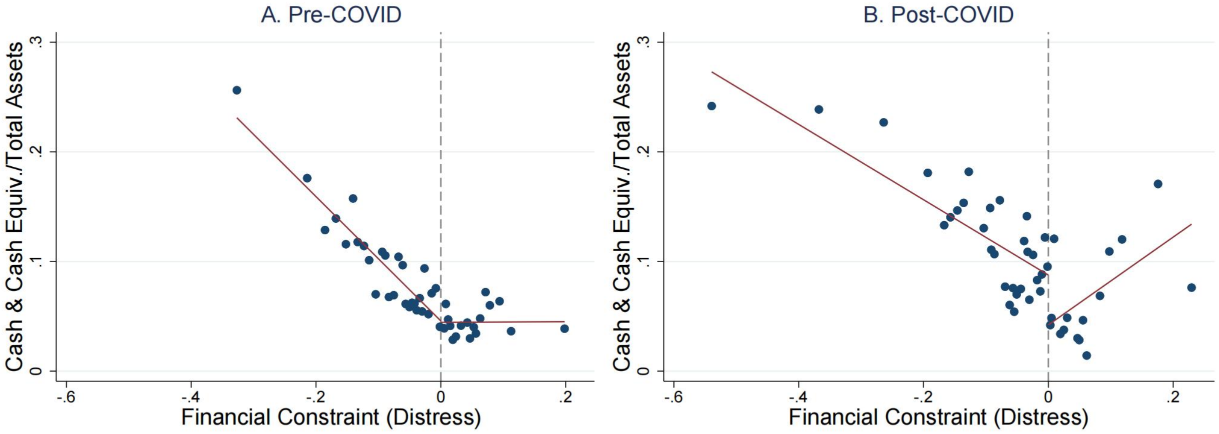

Figure 5. The diagram on the left-hand-side shows a regression-discontinuity design (RID) of cash and cash equivalents against financial constraint (distress) before COVID. The horizontal axis shows the distress ratio, and the vertical axis shows the cash and cash equivalents relative to total assets. The diagram on the right shows the RID after the pandemic outbreak. In addition, the horizontal axis presents the distress, and the vertical axis presents the cash and cash equivalents scaled by total assets.

	Drawdown Size				Credit Line Usage			
	(1) All Firms	(2) Low Distress	(3) Medium Distress	(4) High Distress	(5) All Firms	(6) Low Distress	(7) Medium Distress	(8) High Distress
Distress_t	0.222***	0.275**	-0.069	0.869***	0.387***	0.977***	-0.808*	1.049***
	(0.046)	(0.125)	(0.156)	(0.100)	(0.117)	(0.312)	(0.416)	(0.282)
$\text{Distress}_t \times$2020:Q2	-0.175***	-0.266**	0.186	0.304	-0.276**	-0.937***	0.840	0.683
	(0.050)	(0.127)	(0.434)	(0.235)	(0.127)	(0.317)	(1.155)	(0.662)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	804	239	418	146	788	231	413	143
Adjusted R^2	0.044	0.068	0.021	0.455	0.025	0.067	0.028	0.192

Table 6. **Drawdowns on Financial Distress by Firm Types.** The table provides the baseline regressions of credit line drawdowns on the financial distress by different firm types. In columns (1) through (4), the dependent variables are the ratio of drawdown size (*Drawdowns/total Assets*). In columns (5) through (8), the dependent variables are the usage of credit lines. The independent variables are the distress and the interaction between the distress and the *2020:Q2* dummy. Apart from the regression on the whole sample (columns (1) and (5)), the regressions are also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

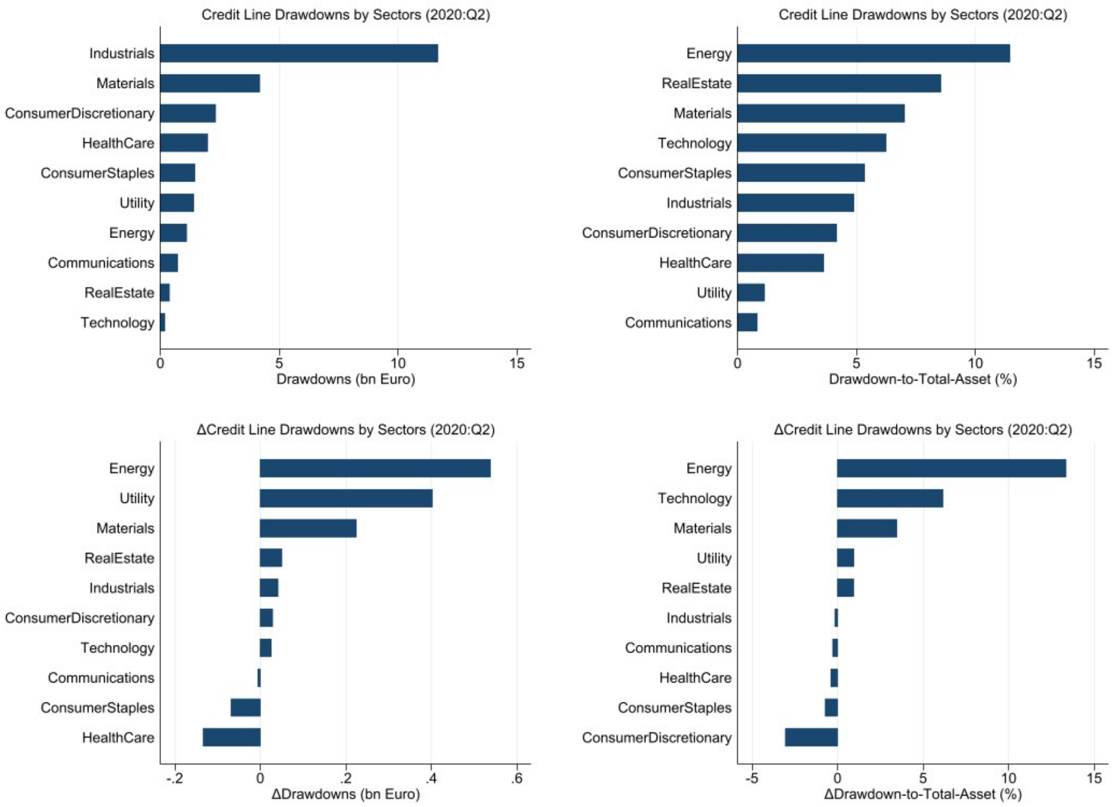

Figure 6. The top left diagram shows credit line drawdowns in different sectors during the second quarter of 2020, followed by similar quarterly changes between 2020:Q1-Q2. The diagram on the bottom-left shows the changes in credit line drawdowns in 2020:Q2, compared with the previous quarter. The horizontal axis shows the changes in the number of drawdowns in billion euros. The vertical axis shows different sectors. The diagram on the right shows the changes in drawdown size in 2020:Q2, compared with the previous quarter. The horizontal axis shows the changes in the drawdown to total assets in percentage. The vertical axis shows different sectors. The sectors Energy, Materials and Utilities increased their drawdown levels in a significant way during the shock, which suggests that firms in these sectors are those more exposed to the 2020:Q2 shock and topped up cash through credit line drawdowns.

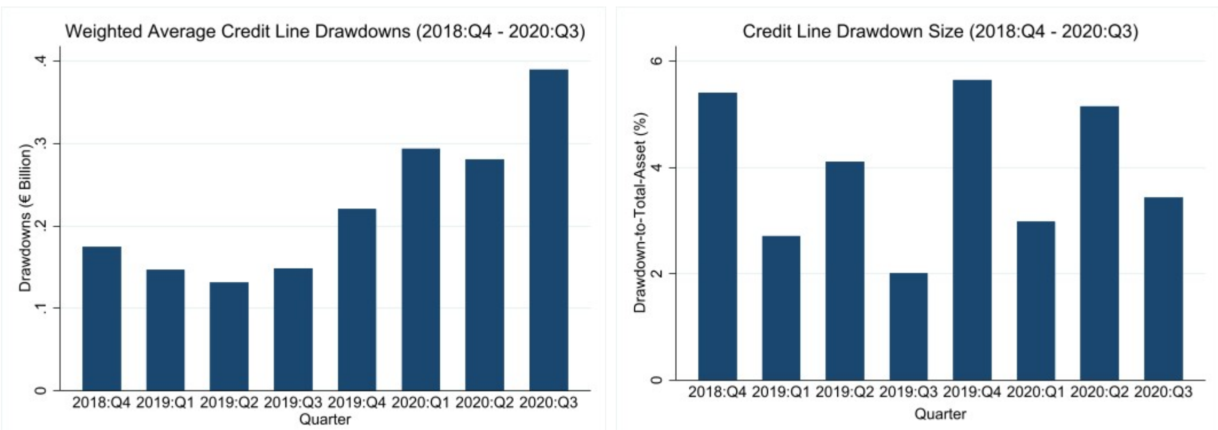

Figure 7. The left diagram reports the average credit line drawdowns at the company level during 2018:Q4 - 2020:Q3. The right diagram reports the drawdowns scaled by total assets during the same period.

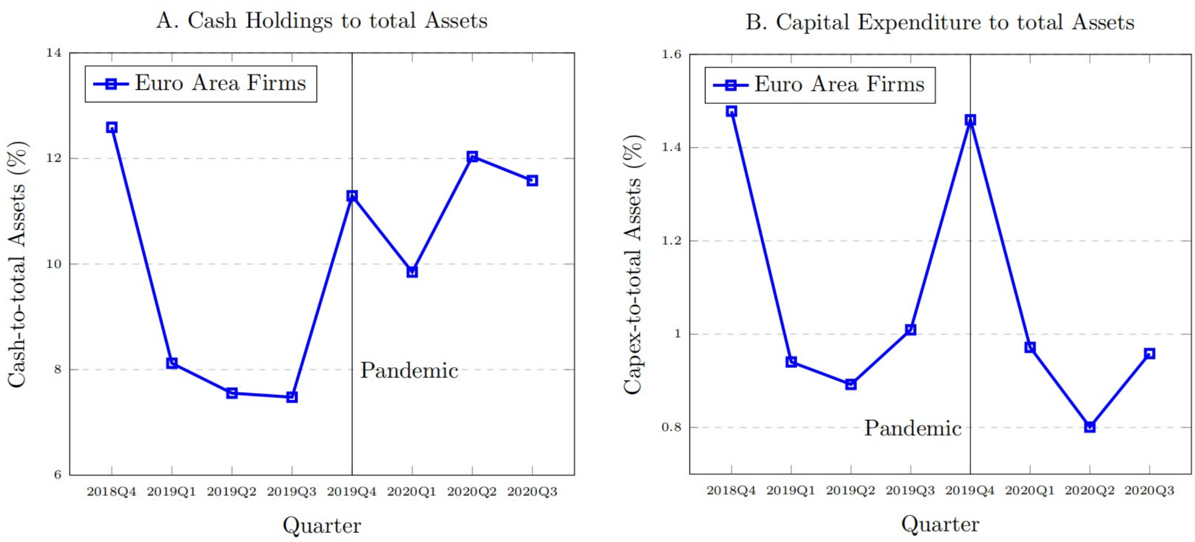

Figure 8. The left diagram reports the average cash-to-total-assets ratio in the firm level during 2018:Q4 - 2020:Q3. The right diagram reports the average capital-expenditure-to-total-assets ratio in the firm level during the same period. The horizontal axes in two diagrams are the quarters, while the vertical axes are the percentage number.

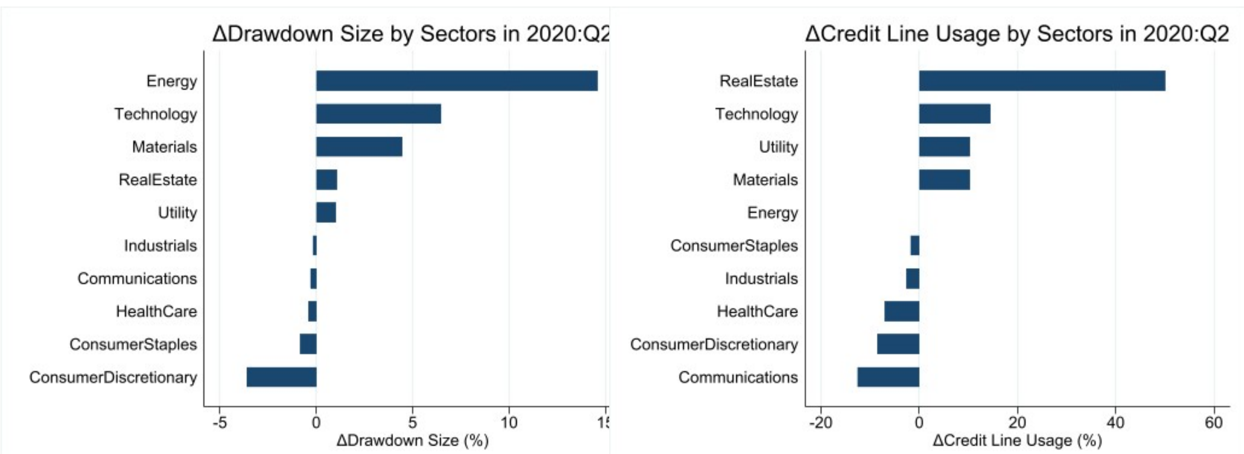

Figure 9. The diagram on the left shows the absolute difference in drawdowns between 2020:Q1-Q2 as a percentage of firms' total assets, whilst the diagram on the right shows firms' credit line utilization difference over the same time period, as a percentage of the firms' total assets.

	Drawdown-to-Total Assets			Credit Line Usage-to-Total Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 2020:Q1			
Distress$_t$	0.095***	0.082***	0.097***	0.200***	0.143**	0.202***
	(0.025)	(0.022)	(0.025)	(0.070)	(0.064)	(0.070)
Cash Holdings$_t$	0.084		0.078	0.333**		0.327*
	(0.057)		(0.057)	(0.169)		(0.170)
Distress$_t \times$2020:Q1		-0.162	-0.144		-0.234	-0.163
		(0.138)	(0.139)		(0.422)	(0.423)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.031	0.032	0.021	0.016	0.020
			Panel B: 2020:Q2			
Distress$_t$	0.095***	0.139***	0.240***	0.200***	0.187*	0.417***
	(0.025)	(0.035)	(0.047)	(0.070)	(0.103)	(0.133)
Cash Holdings$_t$	0.084		0.218***	0.333**		0.531***
	(0.057)		(0.067)	(0.169)		(0.198)
Distress$_t \times$2020:Q2		-0.097**	-0.188***		-0.076	-0.283*
		(0.044)	(0.052)		(0.126)	(0.148)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.035	0.047	0.021	0.016	0.024
			Panel C: 2020:Q3			
Distress$_t$	0.095***	0.081***	0.096***	0.200***	0.131**	0.194***
	(0.025)	(0.022)	(0.025)	(0.070)	(0.064)	(0.070)
Cash Holdings$_t$	0.084		0.080	0.333**		0.354**
	(0.057)		(0.057)	(0.169)		(0.170)
Distress$_t \times$2020:Q3		-0.102	-0.082		0.299	0.390
		(0.128)	(0.129)		(0.368)	(0.370)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.030	0.031	0.021	0.017	0.021

Table 7. **Drawdowns and Liquidity Distress**. This table shows the results of the baseline models in Equation (6). The dependent variable in columns (1) to (3) is credit line drawdowns scaled by total assets. The dependent variable in columns (4) to (6) is credit line usage. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between distress and time dummies (*2020:Q1-Q3*). Panel A shows the interaction between distress and *2020:Q1*. Panel B shows the interaction between distress and *2020:Q2*. Panel C shows the interaction between the and *2020:Q3*. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Drawdown Size			Credit line Usage		
	(1) All Firms	(2) Low Distress	(3) High Distress	(4) All Firms	(5) Low Distress	(6) High Distress
EBITDA_t	-0.129	-0.138	0.969	-0.788*	-0.903**	2.872
	(0.144)	(0.150)	(0.682)	(0.416)	(0.426)	(2.078)
$\text{EBITDA}_t \times$2020:Q2	-1.198**	-0.922	-2.822**	-3.139**	-1.216	-10.093***
	(0.514)	(0.642)	(1.189)	(1.458)	(1.784)	(3.631)
Cash Holdings_t	0.028	0.035	-0.053	0.262	0.277	0.014
	(0.053)	(0.057)	(0.209)	(0.159)	(0.170)	(0.639)
Leverage_t	0.069***	0.077***	0.056	0.172**	0.215***	0.019
	(0.025)	(0.028)	(0.091)	(0.072)	(0.077)	(0.281)
$\log(\text{P/B})_t$	-0.004	-0.006	0.032	-0.014	-0.024	0.080
	(0.005)	(0.006)	(0.022)	(0.015)	(0.016)	(0.066)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	781	687	94	767	675	92
Adjusted R^2	0.029	0.025	0.141	0.034	0.031	0.229

Table 8. **Credit Lines Drawdowns and EBITDA** The table shows firms' reliance on credit lines. The dependent variables are drawdown size (columns 1-3) and credit line usage (columns 3-6). The independent variables include $EBITDA_t$, the earning before interest, taxation, depreciation and amortization, and *2020:Q2*, a dummy equal to one indicating the shock period and zero otherwise. Controls include cash and cash equivalents, the leverage ratio, and the natural logarithm of the price-to-book ratio. Industry- and time-fixed effects are included. Columns (1) and (4) show the estimation results for all the firms, whereas columns (2) and (5) show the results for firms with lower financial distress, and columns (3) and (6) show the results for firms with higher financial distress. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

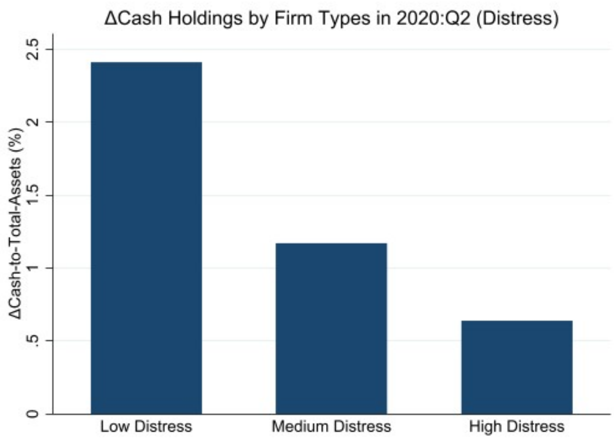

Figure 10. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current scale less the previous one, against different firm types based on the financial constraint (distress). The horizontal axis shows three types of firms: Low Distress (25%), Medium Distress (50%), and High Distress (25%). The vertical axis shows the changes in percentage. Low Distress firms have the highest changes in cash holdings (2.4%), which are nearly twice as high as Medium Distress firms (1.2%) and three times as high as High Distress (0.7%) firms on average.

	Drawdown Size				Credit Line Usage			
	(1) All Firms	(2) Low EBITDA	(3) Medium EBITDA	(4) High EBITDA	(5) All Firms	(6) Low EBITDA	(7) Medium EBITDA	(8) High EBITDA
EBITDA_t	-0.315**	0.278	-2.706***	-0.823**	-1.209***	0.735	-10.151***	-1.395
	(0.138)	(0.322)	(0.805)	(0.322)	(0.431)	(0.966)	(2.627)	(0.956)
$\text{EBITDA}_t \times$ 2020:Q2	-1.357***	-2.760**	3.163	0.427	-3.327**	-7.400**	18.228*	-0.685
	(0.475)	(1.181)	(3.037)	(1.554)	(1.446)	(3.413)	(9.816)	(4.503)
$\log(\text{Assets})_t$	-0.006***	-0.006	-0.005**	-0.011***	-0.022***	-0.036**	-0.019**	-0.027**
	(0.002)	(0.004)	(0.002)	(0.004)	(0.005)	(0.014)	(0.008)	(0.010)
Leverage_t	0.077***	-0.001	0.074**	0.121**	0.146**	0.081	0.130	0.220
	(0.023)	(0.067)	(0.031)	(0.047)	(0.071)	(0.198)	(0.102)	(0.137)
P/B_t	0.000	-0.011*	0.001	0.002	0.001	-0.008	0.009	0.004
	(0.001)	(0.006)	(0.002)	(0.002)	(0.004)	(0.017)	(0.007)	(0.006)
Undrawn CL_t	0.367***	0.504***	0.443***	0.211***	-0.261**	-0.293	-0.407**	-0.086
	(0.034)	(0.083)	(0.053)	(0.056)	(0.105)	(0.244)	(0.173)	(0.163)
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	781	186	389	206	767	180	382	205
Adjusted R^2	0.177	0.220	0.201	0.156	0.057	0.062	0.060	0.114

Table 9. **Credit Lines Drawdowns and EBITDA by firm types.** This table shows the results of the baseline models in Equation (6) within different sub-samples based on firm types. The dependent variable in columns (1) to (4) is credit line drawdowns scaled by total assets. The dependent variable in columns (5) to (8) is the usage of credit lines. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between the distress and time dummies (*2020:Q2*). Apart from the whole sample (columns (1) and (5)), the regression is also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Panel A: Credit Line Usage			
Exposed×2020:Q2	0.091*		
	(0.047)		
Unexposed×2020:Q2		-0.225***	
		(0.075)	
Mild×2020:Q2			0.165**
			(0.078)
Controls	yes	yes	yes
Industry FE	yes	yes	yes
Observations	800	800	800
Adjusted R^2	0.037	0.067	0.040
Panel B: Investment (Capex-to-total Assets)			
Exposed×2020:Q2	-0.003		
	(0.002)		
Unexposed×2020:Q2		-0.002	
		(0.003)	
Mild×2020:Q2			-0.007***
			(0.003)
Controls	yes	yes	yes
Industry FE	yes	yes	yes
Observations	917	917	917
Adjusted R^2	0.122	0.120	0.127
Panel C: Cash Holdings (Cash-to-total Assets)			
Exposed×2020:Q2	-0.012		
	(0.013)		
Unexposed×2020:Q2		0.048**	
		(0.021)	
Mild×2020:Q2			0.036*
			(0.020)
Controls	yes	yes	yes
Industry FE	yes	yes	yes
Observations	1100	1100	1100
Adjusted R^2	0.443	0.441	0.437

Table 10. **Regression Result: Industrial Exposure to 2020:Q2 Shock (Euro Area)**. The dependent variables are credit line usage in Panel A, capital expenditure scaled by total assets in Panel B, and cash holdings scaled by total assets in Panel C. The independent variables contain three dummies: *Exposed*, *Unexposed*, and *Mild*. *Exposed* is the sector with a score higher than 0.75. *Unexposed* stands for the sector with a score lower than 0.3. *Mild* is the sector with a score between 0.3 and 0.75. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix A. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendices

A Description of Variables

Variable	Description
Capex	Purchases of tangible fixed assets, scaled by the total assets (Bloomberg).
Cash Holdings	Cash in vaults plus deposits in banks, including short-term investments with maturities < 90 days, scaled by the total assets (Bloomberg).
Credit Line Usage	The drawn amount of credit lines divided by the total committed amount (Bloomberg).
Credit Ratings	Rating class based on S&P Issuer Rating, such as *AAA-A*, *BBB*, or *Non-IG* (Bloomberg).
Distress	Liquidity distress: (short-term debt $-$ cash holdings $-$ net income)/total assets (Bloomberg).
Drawdown Size	Credit line used, equivalent to the difference between total and undrawn credit lines scaled by the total assets (Bloomberg).
EBITDA	Net income with interest, taxes, depreciation, and amortization, commonly used as a measurement of cash flow by commercial banks. Divided by total assets (Bloomberg).
Exposure	The labour effect of the pandemic on industry indexes O*Net from Dingel & Neiman (2020).
Free Cash Flow	Cash flow less capital expenditure, scaled by total assets (Bloomberg).
High Exposure	Equal to 1 each quarter the country is in the top 50% of confirmed COVID cases per million and 0 elsewhere (European Centre for Disease Prevention and Control (ECDC) from Campello et al. (2020)).
I(Exposure)	Equal to 1 if Exposure ≥ 0.75, 0 if ≤ 0.3 (O*Net from Dingel & Neiman (2020)).
Leverage	The total amount of debt relative to total assets (Bloomberg).
Log(Assets)	The natural logarithm of the total assets (Bloomberg).
Log(Cases)	The natural logarithm of confirmed cases per million (ECDC).
Log(P/B)	The natural logarithm of the stock price to book value per share (Bloomberg).
Log(Stringency)	The natural logarithm of the stringency index, recording social distancing strictness across European countries (Our World in Data from Ritchie et al. (2020)).
Net Income	Profit after expenses (Bloomberg).
RID	Risky-investment-to-debt ratio: $1 -$ book value/[total assets $-$ cash holdings] (Bloomberg).
Short-term Debt	Short-term debt (Bloomberg).
Tangible Assets	Total assets minus intangible assets, scaled by the total assets (Bloomberg).
Undrawn CL	Total remaining amount of committed credit line, scaled by total assets (Bloomberg).

Table A1. **Description of Variables**.

B Alternative Regression Discontinuity Design

We provide additional empirical results using a novel setting proposed by Malenko & Shen (2016). We show that following the 2020:Q2 shock, companies' degree of exposure to the 2020:Q2 shock as measured by earnings and work flexibility provides essential insights into liquidity demand:

$$\begin{aligned} Drawdown_{i,t} &= \phi_0 + \phi_1 EBITDA_{i,t} + \phi_2 BelowCutoff_{i,t} + \phi_3 EBITDA_{i,t} \times \mathit{2020{:}Q2} \\ &\quad + \phi_4 BelowCutoff_{i,t} \times \mathit{2020{:}Q2} + \phi_5 BelowCutoff_{i,t} \times EBITDA_{i,t} \\ &\quad + \phi_6 BelowCutoff_{i,t} \times EBITDA_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{7}$$

where

$$BelowCutoff_t = \begin{cases} 1 & \textit{if Free Cash Flow}_t \in [-\lambda, 0) \\ 0 & \textit{if Free Cash Flow}_t \in [0, \lambda] \end{cases} \tag{8}$$

where λ denotes the bandwidth, which is equal to half the standard deviation of *Free Cash Flow*$_t$ ($\lambda = 0.5\sigma$). Following Malenko & Shen (2016), we define an indicator variable *BelowCutoff* equal to one if the free cash flow is below 0 but considered within the bandwidth and zero otherwise.

The main parameter of interest is β_6, which we expect to be negative and statistically significant, indicating that shocks on EBITDA explain the decisions of a group of companies (i.e. the ones whose EBITDA falls within the range) to draw down credit lines.

Regardless of the inclusion of a fixed effect in the model, there is robust evidence that firms' credit line drawdowns to total assets ratios increased during the pandemic. Figure (3) shows the individual drawdown effects based on Equation (1) where the horizontal axis shows the bandwidth selections versus credit lines drawdowns in percentage points on the vertical axis and their associated 95% confidence intervals. Given the narrowest bandwidth choice of $\pm 0.5\sigma$ surrounding the threshold, drawdown decisions are strikingly different, with the difference remaining statistically significant and retaining its economic size under alternative scenarios. Figure (4) shows the same effect based on the results in Table (B1).

Dependent Variable: Drawdown Size								
	$\lambda = 0.5\sigma$		$\lambda = 0.75\sigma$		$\lambda = \sigma$		$\lambda = 1.25\sigma$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{EBITDA}_{i,t}$	-0.991***	-0.948***	-0.848***	-0.808***	-0.895***	-0.824***	-0.822***	-0.744***
	(0.318)	(0.322)	(0.272)	(0.276)	(0.242)	(0.246)	(0.239)	(0.243)
$\text{BelowCutoff}_{i,t}$	-0.037**	-0.037**	-0.019	-0.018	-0.017	-0.017	-0.014	-0.013
	(0.015)	(0.016)	(0.014)	(0.014)	(0.012)	(0.013)	(0.012)	(0.012)
$\text{EBITDA}_{i,t}\times$2020:Q2	0.428	0.475	-0.105	-0.071	-0.292	-0.266	-0.355	-0.343
	(0.706)	(0.707)	(0.592)	(0.592)	(0.494)	(0.492)	(0.500)	(0.498)
$\text{BelowCutoff}_{i,t}\times$2020:Q2	0.059**	0.065***	0.040*	0.043**	0.038*	0.041**	0.031	0.034*
	(0.025)	(0.025)	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.020)
$\text{BelowCutoff}_{i,t}\times\text{EBITDA}_{i,t}$	0.906*	0.782	0.600	0.474	0.640	0.554	0.575	0.484
	(0.486)	(0.493)	(0.441)	(0.447)	(0.391)	(0.395)	(0.382)	(0.386)
$\text{BelowCutoff}_{i,t}\times\text{EBITDA}_{i,t}\times$2020:Q2	-3.262***	-3.349***	-2.564**	-2.446**	-2.412**	-2.370**	-2.287**	-2.281**
	(1.169)	(1.185)	(1.068)	(1.069)	(0.990)	(0.988)	(1.001)	(0.998)
$\log(\text{Assets}_{i,t})$	-0.010***	-0.009***	-0.010***	-0.011***	-0.008***	-0.008***	-0.009***	-0.009***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\text{Leverage}_{i,t}$	0.068**	0.081**	0.066**	0.084***	0.064***	0.076***	0.058**	0.067***
	(0.030)	(0.032)	(0.027)	(0.028)	(0.024)	(0.025)	(0.024)	(0.024)
Undrawn $\text{CL}_{i,t}$	0.321***	0.336***	0.256***	0.268***	0.263***	0.280***	0.237***	0.253***
	(0.048)	(0.049)	(0.043)	(0.044)	(0.039)	(0.040)	(0.037)	(0.037)
$\log(\text{Price}_{i,t})$	0.009**	0.010**	0.005	0.005	0.003	0.003	0.004	0.004
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)
Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	328	328	458	458	544	544	596	596
Adjusted R^2	0.240	0.247	0.159	0.170	0.151	0.162	0.130	0.142

Table B1. **Alternative Regression Discontinuity Design on Drawdowns**. This table shows an alternative regression discontinuity design of credit line drawdowns on the EBITDA. The dependent variable is *Drawdown Size*, indicating the credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, *BelowCutoff*, a dummy equal to one that the firms have performance just below the cut-off point, and zero the firms are just above the cut-off point, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included as indicated. Columns (1), (3), (5), (7), and (9) use sub-samples based on the performance just below the threshold. The rest columns use sub-samples based on the performance just above the threshold. σ denotes the standard deviation of the performance. A real number multiplying σ (for example, -0.5σ) represents the direction and distance away from the threshold. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C First Stage Results

In this Appendix, we provide the results of the first-stage regression in Equation (2). Results are reported in the table below and show that whether a firm is highly exposed affects its cash flow and, therefore, influences its credit line drawdowns.

	EBITDA
	(1)
	Table 4
I(Exposure)	-0.009***
	(0.002)
Observations	881
Adjusted R^2	0.018

Table C1. **First Stage.** R provide F-statistics The table provides the first-stage regressions of column (5) in both Table (4) & Table (**??**). In columns (1) and (2), the dependent variables are the cash flow measured by earnings before interest, taxes, depreciation, and amortization (EBITDA). The independent variable is a dummy equal to one that a firm is highly exposed to the 2020:Q2 Shock, and zero otherwise. All variables are defined in Appendix A. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Declarations

Conflict of interest There is no conflict of interest.

Research Data Availability Statement The data and statistical programme are available on request from the corresponding author. The data are not publicly available due to the data providers' terms and licensing restrictions.