European firms, Panic Borrowing and Credit Lines Drawdowns: What did we learn from the COVID-19 Shock?

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November 6, 2022

Abstract

We show that European firms, at the peak of the COVID-19 shock identified in 2020:Q2, went into a sort of panic borrowing status and drew down €87bn in a very short period. We show that firms with less stringent solvency and liquidity constraints drew down their credit lines and accumulated cash. We use COVID-19 infection data and proxies for social distancing policies across Europe to study if the increase in aggregate risk introduced by the COVID-19 shock can explain the panic borrowing while accounting for possible endogenous credit lines drawdowns. Finally, we show that European corporate drawdowns during the pandemic crisis increased on average by 3.35 percentage points in response to an unexpected one percentage point fall in their cash flows but only when firms' earnings are negative, and the lockdown drives this.

Keywords: Corporate credit lines, cash holding, investment, default risk
Classification codes: G21, G32, G33

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1 Introduction

Over the past decade, credit lines have channelled a significant amount of credit from banks to European enterprises. For example, we estimate that European firms drew about €87bn, in a short time, during the pandemic crisis to stay afloat. It was an unprecedented fly to liquidity on a macroeconomic scale during which 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). Recently Acharya et al. (2020) showed the same fly-to-liquidity for US firms. Why did European firms draw down their credit lines at the start of the pandemic shock identified in 2020:Q2? Theoretical models would predict that firms draw from credit lines to finance investments as an alternative to cash. Did we find this evidence for European firms? More important, which firms drew down credit lines, and accumulated cash? Answering these questions is very important not just from a policy perspective but also in modelling liquidity risk in corporate liquidity management. For example, corporate liquidity risk management models do not consider using credit lines for cash accumulation (what we call panic borrowing) and, therefore, a possible endogenous role of credit line drawdowns in firms' decisions. We contribute empirically to shed light on this issue in several ways by using COVID-19 data and proxies for mobility across Europe and employing quasi-natural experiments.

The COVID-19 shock led to a policy response across Europe which was not uniform (we call this country flexibility). The social distancing policies adopted by European countries were very different, in different countries, and this may have had implications for firms' liquidity risk management. Ours is the first paper to study this issue using actual COVID-19 infection rates across Europe and a proxy for measuring the strictness of social distancing policy in a country (Oxford Stringency Index). It shows that country flexibility is vital as firms in countries where COVID-19 infection rates were higher and social distancing policies stricter went into a "panic borrowing" and drew down their credit lines. We also extend our study to consider work flexibility and credit line drawdowns. Campello et al. (2020) show for the US that work flexibility is essential to understand the job hiring market in the US during the COVID-19 period. We extend this to the European market and firms' liquidity risk management during the COVID-19 shock. We show that work flexibility is vital to understand firms' behaviour, that is, the "panic borrowing". Finally, we show that the "panic borrowing" amongst European firms and work flexibility are unique to the COVID-19 crisis and do not extend to either the 2008 financial crisis or the 2012 European crisis. The panic borrowing observed in Europe seems unique to the COVID-19 crisis. These are also new and significant results as they suggest that the nature of the aggregate risk (COVID-19 shock vs financial crisis shock) does matter to understand why European firms draw down credit lines and accumulate cash. Our results suggest a novel interplay between social distancing rules, a fall in revenues and credit lines drawdown for precautionary reasons. This new mechanism also has important implications for banks when granting credit to firms. It introduces a new source of risk for banks (social distancing policies and work flexibility) associated with firms' idiosyncratic risk.

Although some of our results in the first part of the paper are consistent with the US as documented in Acharya et al. (2020), suggesting a higher degree of international corporate market integration, we also assume an endogenous role for credit lines in firms' liquidity management. We, therefore, employ robust econometric settings and real COVID-19 infection rates. In doing so, our results complement and extend Acharya et al. (2012), Campello et al. (2011), and Acharya et al. (2020).

Credit lines are financial contracts enabling firms to draw funds from their bank accounts and have financing available as contingent liquidity provisions to offset shocks. Hence, credit lines are contingent liquidity lines which can be viewed as insurance against unexpected future liquidity requirements. This funding vehicle is crucial in Europe given the high reliance of European firms on bank-based financing, further underscoring its significance relative to alternative capital market-based financings in the US. Furthermore, our study on European firms complements others (for example, Acharya et al. (2020)) and allows us to study international financial and corporate markets integrations as pointed out in Berg et al. (2017).

Figure (1) shows the total amount (in billions of euros) of credit lines drawn by European firms, across different sectors, in 2020:Q2. Contrary to alternative reports, we estimate that a total of €87bn were taken out of credit lines between 2020:Q1 and 2020:Q2 and the largest part, €49bn, was taken out of credit lines in 2020:Q2 alone. Figure (1) shows that industrials and materials were the sectors that relied significantly on credit lines in 2020:Q2 in terms of the total credit value, whilst energy, real estate and materials are amongst the top three sectors using credit lines to finance operations. The lower panel depicts quarterly changes where energy, utilities and materials have further increased their reliance on credit lines. In contrast, energy, technology and materials have marginally increased their drawdown to total assets ratios during 2020:Q2 relative to the previous quarter.

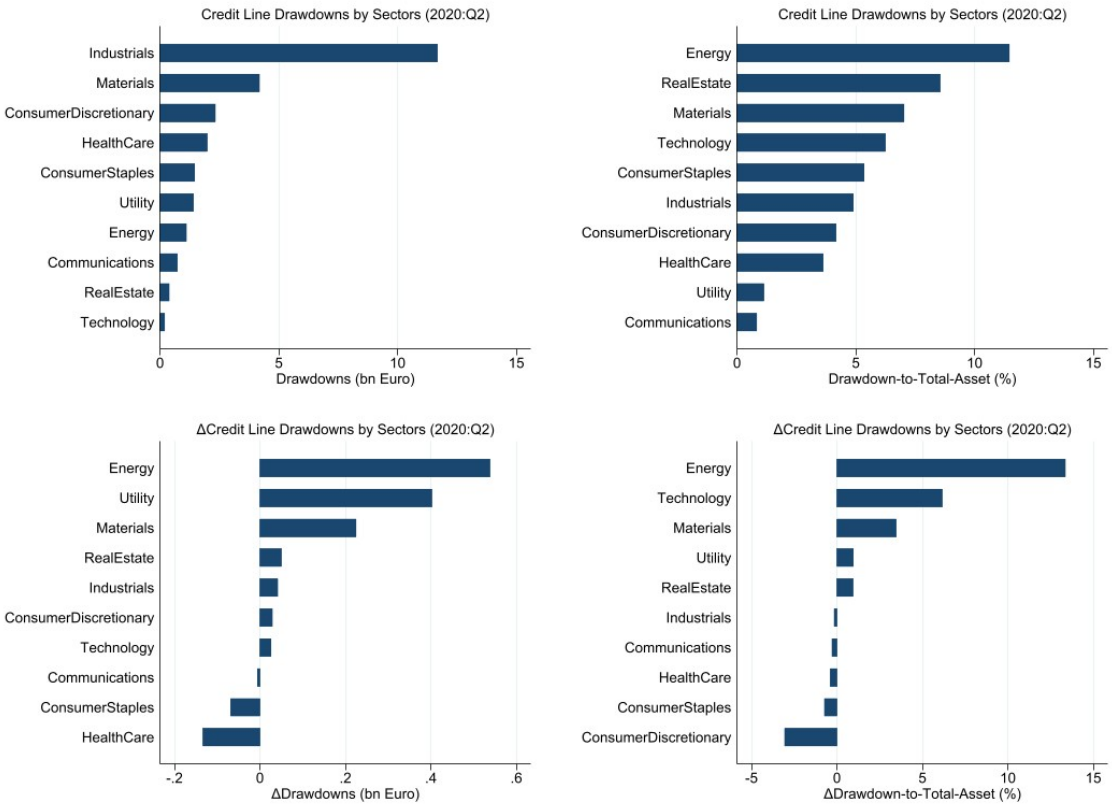


Figure 1. The top left diagram shows credit line drawdowns in different sectors during the second quarter of 2020, followed by similar quarterly changes between 2020:Q1-Q2. The diagram on the bottom-left shows the changes in credit line drawdowns in 2020:Q2, compared with the previous quarter. The horizontal 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 COVID-19 shock and topped up cash through credit line drawdowns.

Sufi (2009) studies the substitution effect between internal (cash/cash holdings) and external (credit lines) fundings using data when credit was abundant and shows that firms using credit lines are generally profitable firms. Campello et al. (2011), using data for the 2008 financial crisis and US firms confirms a substitution effect between cash holding and credit lines when firms face a severe credit shortage. We extend and complement these studies by studying European firms during the COVID-19 shock with the main focus on external borrowing via credit lines as this part of the literature is more limited and, critically, studying why firms draw down their credit lines to accumulate cash.

If we consider the COVID-19 shock, while Li et al. (2020) and Greenwald et al. (2021), for the US market, show that firms used credit lines to support investments, Bosshardt & Kakhbod (2020), and Acharya et al. (2020), again for the US market, show that firms drew down credit lines for precautionary reasons. We also contribute to this recent literature by studying firms' financing behaviour in the presence of solvency and liquidity constraints during the COVID-19 period. We also show that European firms did not draw down credit lines for investment. They accumulated cash and also studied why that happened.

Acharya et al. (2012) show that the literature investigating the precautionary motive for holding cash may have produced misleading results due to the endogeneity of cash holdings and credit risk. They show that high credit rating firms behave similarly to more financially constrained firms (lower credit quality firms) in holding cash. We speak to this literature as we explicitly consider solvency and liquidity constraints for European firms during the COVID-19 shock. We also empirically extend this literature by considering endogeneity between credit risk and cash accumulation as discussed in Acharya et al. (2012), but also between credit risk and credit lines drawdowns. This literature is limited. We design a battery of ad-hoc econometric methodologies to study this.

Papanikolaou & Schmidt (2022) find that the COVID-19 shutdown had a heterogeneous effect across firms due to the degree of opportunity to work from home (work flexibility). They find that firms with fewer opportunities to work from home performed worse, as measured by a fall in expected revenue and credit quality deterioration. We show that European firms hit mainly by the COVID-19 shock saw their expected revenues, as measured by EBITDA, fall. These firms increased credit line drawdowns and then their cash holdings. Following Campello et al. (2011, 2020), we study this relationship by introducing work and country flexibility as possible explanations for firms' "panic borrowing".

2 Data

We collect credit lines data from Bloomberg and, unless mentioned, use all the firms with available information between 2018:Q4 and 2020:Q3. We exclude financial companies, including banks, investment and insurance companies, private equity companies, security and commodity exchange and wealth management companies and focus on firms within the Euro area where there are 324 non-financial firms in total between 2018:Q4 to 2020:Q3.

We use credit line drawdown and the total amount of committed credit lines. Specifically, the total credit line refers to the total amount of committed lines of credit that firms can access. The available credit line is the remaining amount that a bank (financial institution) has agreed to lend and is equivalent to the undrawn amount of the credit line. The drawdown share of the credit lines is calculated as the total credit line minus the undrawn credit line. We supplement credit line data by including firms' financial variables from Bloomberg. The industry classification used in this paper is based on the Bloomberg Industry Classification System (BICS).[1]

Table (1) shows the summary statistics between 2018:Q4-2020:Q3 with 1,157 credit facility observations. The credit line usage and the undrawn rates are 19.1 and 80.9 per cent, respectively.[2] The drawdown size, drawdown-to-non-cash assets ratio, is about 5 per cent and the undrawn size, undrawn amount of credit line scaled by non-cash assets, is about 12 per cent.

Following Sufi (2009), we use non-cash assets as a scale instead of total assets to mitigate the potential influence of cash holdings on drawdowns. We adjust some financial variables by non-cash assets, the total assets excluding cash and cash equivalent. Accordingly, *Cash Holdings* represents the cash and cash equivalent scaled by non-cash assets. *Cash Flow*, *CAPEX*, and *Tangible Assets* are cash flow, capital expenditure and tangible assets scaled by non-cash assets separately. *Log(assets)* is the natural logarithm of non-cash assets.

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Cash Holdings	1,157	0.107	0.116	0.000	0.041	0.076	0.142	1.949
CAPEX	969	0.012	0.012	0.000	0.004	0.009	0.016	0.175
Credit Line Usage	827	0.191	0.277	0.000	0.000	0.000	0.350	1.000
Drawdown Size	842	0.051	0.108	0.000	0.000	0.000	0.041	0.758
Cash Flow	1,055	0.028	0.031	-0.372	0.016	0.027	0.040	0.268
Undrawn Size	1,133	0.117	0.108	0.000	0.046	0.090	0.148	0.923
Undrawn Capacity	827	0.809	0.277	0.000	0.650	1.000	1.000	1.000
P/B Ratio	1,130	3.731	45.989	0.014	1.062	1.683	2.745	1,545
Log(assets)	1,157	21.420	2.075	15.531	19.915	21.558	22.783	26.859
Tangible Assets	1,144	0.838	0.272	0.001	0.659	0.887	1.013	2.938
Leverage	1,157	0.302	0.169	0.000	0.190	0.283	0.403	1.203

Table 1. Summary Statistics

Revolving credit lines are the facilities most commonly used by banks to supply funds to firms. Figure (2A) shows credit line draw-downs and the total committed amount of credit lines for all Euro-area firms in the sample. Figure (2B) shows the draw-down of credit lines scaled by the number of firms in each quarter.[3] There is significant access to credit lines by EU firms at the start of the pandemic and in the following months.

We note a significant increase in cash holdings during the same period. The increase in cash holdings could be driven either by an expected liquidity shock or to support investments. Figure (3A) shows the trend in liquidity accumulation before and after the pandemic period. Specifically, average cash holdings, including cash and cash-equivalent components, scaled by non-cash assets, increased sharply during the pandemic. The sharp increase in cash holdings is consistent with (Anderson & Carverhill (2012), Bolton et al. (2011)) and suggests an increase in liquid assets to mitigate the impact of liquidity shocks. In other words, EU firms may have taken out of their credit lines in anticipation of a possible liquidity shock. However, credit line draw-downs can also be associated with greater investments. In Figure (3B), we use capital expenditure as a proxy

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

[2]Credit line usage is given by the ratio of drawn-down to the total amount. The undrawn rate is equivalent to one minus credit line usage.

[3]For example, 286 firms had, in total, 279.465b euros in committed credit lines at the end of 2018:Q4, and the average committed amount is €279.465b / 286 = €0.977b. In 2019:Q1, only 80 firms showed a total of 63.689b euros in the committed credit line, with the average being 63.689b / 80 = 0.796b euros.

for investment. There is limited evidence that EU firms used credit lines to support investments during the pandemic. Acharya & Steffen (2020*b*) provide empirical evidence for the United States and show that the "dash for cash" of US firms during the pandemic period was mainly driven by precautionary saving reasons. Bosshardt & Kakhbod (2020) show similar evidence.

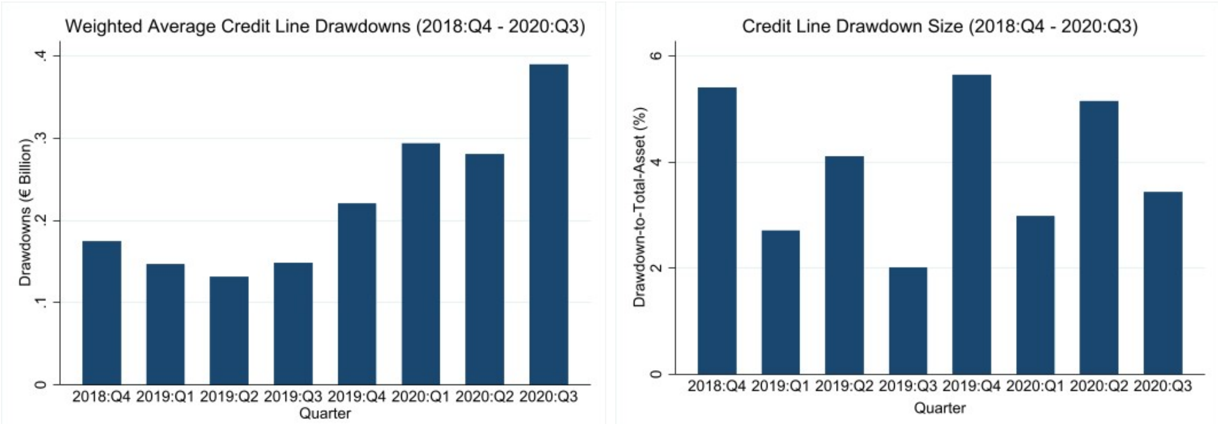


Figure 2. The left diagram reports the average credit line drawdowns in the firm level during 2018:Q4 - 2020:Q3. The right diagram reports the drawdowns scaled by total assets during the same period.

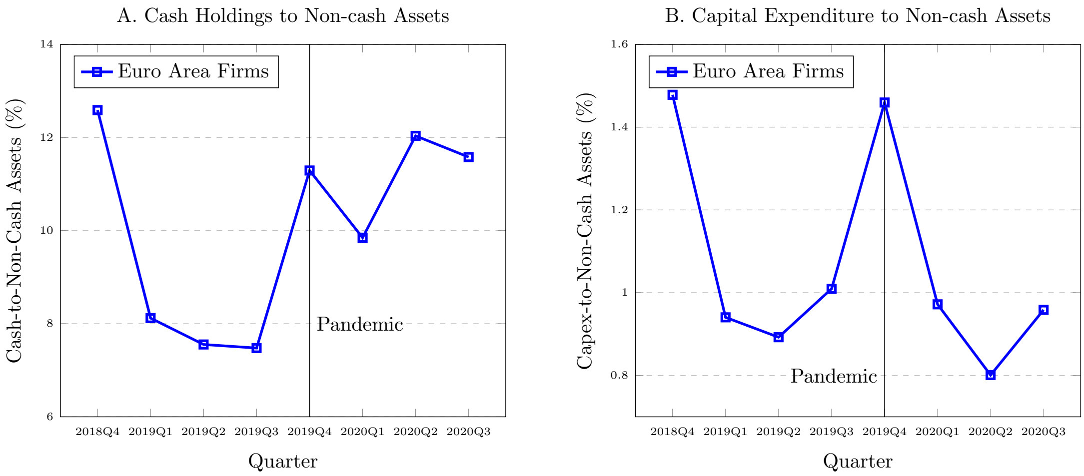


Figure 3. Cash Holdings and Capital Expenditure

3 Financial Constraints

Sufi (2009) shows that, in general, less financially constrained firms rely on credit lines while financially constrained firms use cash. However, Sufi's study investigates a period when credit was abundant, which may have affected results. Campello et al. (2011) study the financial crisis period. Although they show that firms substitute between internal (cash holding) and external liquidity (credit lines) when liquidity shocks hit them, the main focus of that study is on firms' real side effect (investment) decisions when using credit lines. Acharya & Steffen (2020*b*) investigates the recent COVID-19 period focusing on how firms raised cash to offset changes in credit risk increase after the COVID-19 shock. They show that credit risk is important to understand how US firms raised cash during the pandemic and US firms dashed for cash during the pandemic period. Our paper builds and, at the same time, complements Acharya & Steffen (2020*b*) in several ways. Firstly, we directly introduce both solvency and liquidity constraints. Secondly, we consider other important constraints: country and work flexibility. Thirdly, we allow for an endogenous role of credit lines. That is, we conjecture that credit line decisions made by firms at the peak of the pandemic crisis and cash holdings were driven by the unprecedented shock (which increased aggregate risk) introduced by COVID-19. Our paper considers these additional constraints and shows some novel results for European firms.

The paper proceeds as follows. In the first part, we investigate why and how firms raise cash during the pandemic period. In so doing, we contribute to an essential strand of literature studying firms' financial constraints and liquidity accumulation. More importantly, we extend it to study the relationship between firms' financial constraints and credit line drawdowns (external financing) (Acharya et al. 2012), as this literature is somehow more limited.

In the second part of the paper, we study if social distancing rules across European countries (country flexibility) and within industries (work flexibility) help to understand why firms drew down credit lines to accumulate cash. The capacity of a firm to access external financing is heterogeneous across firms, depending, amongst other things, on their underlying current and future capacity to meet liabilities. Unexpected shocks, such as the lockdown during the pandemic period, can produce undesirable outcomes, particularly for the firms affected by social distancing policies. For example, more stringent social distance policies in a given country (less country flexibility) may impact firms' expected cash flow, leading firms to draw down their credit lines and increase cash holdings. (Almeida et al. 2004, Bates et al. 2009). Acharya et al. (2012) show that even firms with lower credit risk in the presence of financial constraints behave similarly to firms with higher credit risk. We find some evidence of this for European firms. In the next section, we shall consider credit risk (firms' solvency) (Acharya et al. 2012).

3.1 Solvency-Driven Credit Line Draw downs

In this section, we empirically study how solvency risk drives firms' decisions to draw down credit lines, focusing on the substitution effect between internal resources (cash holdings) and external ones (credit lines) in the presence of solvency constraints. We study the COVID-19 period and European firms. In general, constrained firms tend to hold more cash for investment than unconstrained ones (Denis & Sibilkov 2010, Farre-Mensa & Ljungqvist 2016). Acharya et al. (2012) show that US financially constrained firms accumulate more cash for precautionary reasons and that higher cash accumulation, in general, is associated with high credit risk. They show that in the presence of financial constraints (for example, a significant fall in revenue affecting firms' credit risk profile), high cash holdings firms behave the same way as low cash holding firms. More recently, Acharya & Steffen (2020*a*) show evidence in support of this for US firms at the start of the COVID-19 period. They also show that financially constrained firms (BBB and Non-IG) drew down their credit lines at an increased speed and accumulated cash at the start of the pandemic crisis. However, only firms whose credit risk profile was quickly deteriorating continued to access credit lines in the second part. In this section, we build on this literature (Whited & Wu 2006, Almeida & Campello 2007, Farre-Mensa & Ljungqvist 2016) and empirically study the relationship between credit line drawdowns (cash holdings) and solvency risk across different firms during the COVID-19 shock.

Table (2) shows an example of a corporate balance sheet. The left-hand side shows total assets and contains cash, cash equivalent and risky investment.[4] The right-hand side shows the liabilities

[4]Risky investment contains long-term investment and fixed assets, equal to total assets minus cash and cash

and shareholders' equity, consisting of (total) debt and equity. The total amount on the left-hand side should equal that of the right-hand side. We assume that the firm has to cover its cost of debt using all the returns on total assets when facing a financial or pandemic crisis. The total amount on the left-hand side, return on cash and cash equivalent plus return on a risky investment, and the one on the right-hand side, cost of debts, are also balanced.

<table>
<tr><th>Assets</th><th>Liabilities</th></tr>
<tr><td>Cash &
Cash Equivalent</td><td rowspan="2">Debts</td></tr>
<tr><td rowspan="2">Risky
Investments</td></tr>
<tr><td>Equity</td></tr>
</table>

Table 2. Balance Sheet

Assume that A is the total assets, C cash and cash equivalent, I risky investment, D is the total debt, and E is the shareholders' equity. Also, we let R_C, R_I, R_D be the interest rates on cash and cash equivalent, risky investment, and debt, respectively. Based on table (2), total assets, cash and cash equivalent, risky investment, debt, and equity should simultaneously satisfy the balance sheet equation below:

$$C + I = D + E$$

To examine the firm's behaviour in response to default as a result of an unexpected shock to the risky investment, we consider the following solvency condition which expresses an end of period assets value equal to the total debt obligations plus interests:

$$R_C \cdot C + R_I \cdot I = R_D \cdot D$$

The solvency condition expressed above assumes that the firm remains just-solvent while the shareholder value is zero as a result of underperformance of the risky investments. Rearranging the above equations by substituting I and D, we can have

$$R_I \quad = \quad \frac{R_D \cdot (A - E) - R_C \cdot C}{A - C}$$

Suppose that the cost of debt, R_D, is equal to the return on cash and cash equivalent, R_C. Since firms seek to make the rate of return on cash or short-term investment at least equal to the interest rate of liability, we can rewrite the expression above as:

$$\frac{R_I}{R_D} \quad = \quad 1 - \frac{E}{A - C} \tag{1}$$

The left-hand side shows the profitability of risky investments, or non-cash assets, to hedge the interest rate of total debts. The right hand side is the relationship between equity E and risky investment $(A - C)$. In other words, it shows that profitability is determined by the proportion of equity value to risky investment. We, therefore,call the ratio R_I/R_D the risky-investment-to-debt ratio (RID). For example, assume that the rate of debt is 5%. If RID is 0.9, it means that the rate of return on all the risky investments should be at least 4.5% (5% $\times$ 0.9) to hedge the debts. If

equivalent, namely, non-cash assets. This type of asset is far less liquid than cash. Investors or firms cannot convert them immediately when facing a liquidity shortfall.

RID falls, less return on risky investment is needed to compensate for debt. Therefore, a fall in the RID can imply that a less risky investment is needed to maintain the debt coverage, given constant equity.

To study the association between solvency ratio (RID) and credit line drawdowns, we use two approaches. First, we use the drawdown amount of credit lines scaled by non-cash assets, namely, the drawdown size. Subsequently we also use credit line usage. We employ the following model:

$$\begin{aligned} \textit{Drawdown}_{i,t} &= \alpha + \beta_1 \textit{RID}_{i,t-1} + \beta_2(\textit{RID}_{i,t-1} \times \textit{2020:Q2}) \\ &\quad + \gamma X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $\textit{Drawdown}_{i,t}$ is (i) drawdown size and (ii) credit line usage. $\textit{RID}_{i,t-1}$ is a variable indicating risky-investment-to-debt ratio:

$$\textit{RID} = 1 - \frac{\textit{Book Value}}{\textit{Total Assets} - \textit{Cash \& Cash Equivalent}} \tag{3}$$

2020:Q2 is a dummy equal to 1 proxying the liquidity shock induced by COVID-19. $X_{i,t-1}$ controls, consisting of the logarithm of non-cash assets, the undrawn credit lines scaled by non-cash assets, the price-to-book ratio, the tangible assets related to non-cash assets, and the leverage ratio.

Table (3) shows the results. Columns 1 to 4 in Table (3) show that the coefficient on RID, β_1, is statistically significant and positive for the full sample. Higher insolvency risk is associated with higher access to credit lines. However, there is a shift in the sign of the coefficient once we consider the interaction coefficient, $\textit{RID}_{i,t-1} \times \textit{2020:Q2}$. Overall, columns 5 and 8 show similar results using credit line usage. The positive coefficient on RID shows that the higher the RID, the lower the solvency (i.e. the credit risk of the firm increases), and the higher the access to credit lines. On the other hand, the negative coefficient on the dummy in 2020:Q2 is interesting as it suggests a negative association between credit line drawdowns and solvency risk.[5] Lower-risk firms drew down credit lines in 2020:Q2.[6] In Panel B of Table (3), we shed further light on this result. We divide firms (in 2020:Q2) into three groups according to the RID: Low Risk (25%), Medium Risk (50%) and High Risk (25%).[7]

The coefficients in the three groups are statistically insignificant based on the full sample. Second, based on 2020:Q2, the only significant coefficient is associated with the Low-Risk group. This coefficient is also negative, which implies that lower-risk firms (in terms of solvency) accessed their credit line in 2020:Q2. Figure (4) shows the change in credit lines between two quarters (for each of the three groups) between 2020:Q1 and 2020:Q2. Figure (4) projects the change in cash holding for the three groups. Low-risk firms are those with the greatest change in cash holding between 2020:Q1 and 2020:Q2. A significant (negative) association exists between credit line drawdown and solvency risk during the pandemic shock (2020:Q2). In a nutshell, firms with a good solvency position drew down their credit lines during the COVID-19 shock and topped up

[5]We also consider possible outliers and the significance increases from 10% to 5%. Results are available upon request

[6]In Appendix (C1), we also include cash holdings as a control variable with a positive and significant sign.

[7]We also examined alternative combinations, and results stay unchanged. Results are available upon request

their cash holding position.[8] In the next section, we consider a liquidity measure.[9]

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Different Dummies								
RID_{t-1}	0.039***	0.038***	0.046***	0.042**	0.119**	0.114**	0.147***	0.101
	(0.013)	(0.013)	(0.014)	(0.017)	(0.050)	(0.050)	(0.052)	(0.064)
$RID_{t-1}\times$2020:Q1		0.031				0.139		
		(0.046)				(0.165)		
$RID_{t-1}\times$2020:Q2			-0.061*				-0.199*	
			(0.032)				(0.109)	
$RID_{t-1}\times$2020:Q3				-0.007				0.040
				(0.024)				(0.089)
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	388	388	388	388	381	381	381	381
Adjusted R^2	0.059	0.057	0.066	0.057	0.057	0.056	0.063	0.055
Panel B: Different Firm Types								
	(1) All Firms	(2) Low Risk	(3) Medium Risk	(4) High Risk	(5) All Firms	(6) Low Risk	(7) Medium Risk	(8) High Risk
RID_{t-1}	0.046***	0.018	-0.127	-0.090	0.147***	0.129	-0.242	0.193
	(0.014)	(0.020)	(0.085)	(0.146)	(0.052)	(0.112)	(0.231)	(0.499)
$RID_{t-1}\times$2020:Q2	-0.061*	-0.173***	0.046	0.092	-0.199*	-0.556*	0.283	0.284
	(0.032)	(0.054)	(0.174)	(0.240)	(0.109)	(0.296)	(0.478)	(0.818)
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	388	83	199	105	381	79	199	102
Adjusted R^2	0.066	0.127	0.019	0.189	0.063	0.017	0.085	0.241

Table 3. **RID Ratio on Drawdowns (Euro Area)** This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the RID ratio and time dummies (*2020:Q1-Q3*), respectively. Panel B shows the baseline models within the whole sample (*All Firms*) and three sub-samples (*Low-*, *Medium-*, and *High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[8] We have also included Cash Holdings in Table (3) and the coefficients are significant but positive. Therefore, we exclude that a substitution effect between internal and external funding may have occurred during the COVID-19 period.

[9] Our analysis also considers an alternative specification where the firm indicators are constructed according to their ratios to total assets. The supplementary estimations reveal that the results remain robust to both specifications presented in Appendix (C1).

Figure 4. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current size less the previous one. The horizontal axis shows three types of firms: low-, medium- and high-risk ones. The vertical axis shows the changes in percentage.

3.2 Credit Ratings and Access to Credit Lines

In Section 3.1, we found that, over the whole sample, there is a positive and significant association between firms' solvency risk and credit lines drawdowns, but this relationship changes at the time of the COVID-19 shock (2020:Q2). Acharya & Steffen (2020*b*) for the US market and the COVID-19 shock, show that firms drew down credit lines at the time of the COVID-19 shock, but the usage rate was higher among non-investment and BBB-rated firms. In the second period, BBB-rated firms still increased access to credit lines and topped up cash holdings. In this section, we replace our measure of firms' solvency with credit ratings and consider changes in firms' credit risk over three quarters (Q1-Q3), that is, before and after the COVID-19 shock (2020:Q2) and credit lines drawdowns.

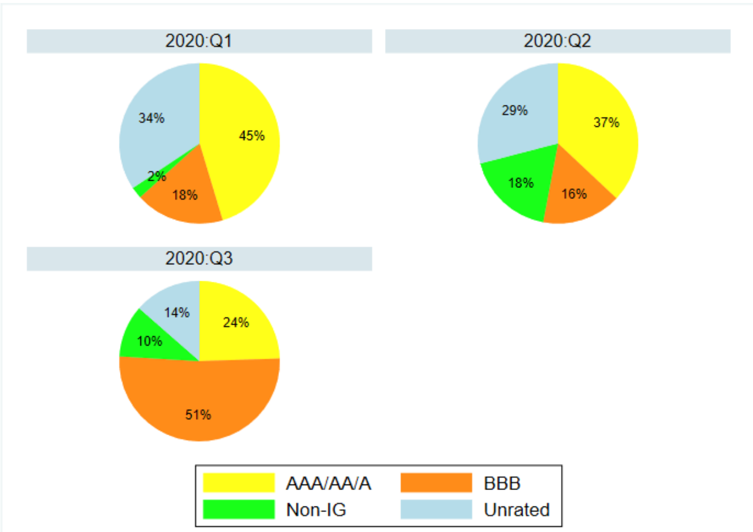


Figure 5. This diagram shows the distribution of credit line drawdowns across credit ratings during 2020:Q1 - Q3.

Figure (5) sheds light on the previous results. Firstly, while between 2020:Q1 and 2020:Q3, AAA-rated firms reduced their access to credit lines, BBB-rated firms increased it. This result is in line with Acharya & Steffen (2020*b*) for the US market. It suggests that the "Fallen Angels" phenomenon (i.e. firms whose credit rating is quickly deteriorating due to COVID-19 shock) is not specific to one country (that is, the US). However, it extends widely, confirming a more substantial degree of international corporate market integration in the presence of unexpected negative shocks.

Overall, Figure (5) is consistent with our previous results showing a negative association between firms' solvency risk and credit lines drawdowns at the pick of the COVID-19 shock.

3.3 Liquidity-Based Constraints

We now turn to the relationship between firms' liquidity constraints and credit line drawdown during the COVID-19 shock. Following the previous literature, amongst other things, we also study the substitution effect between internal and external cash, with a different focus on the COVID-19 period. Did firms with a good liquidity position draw down credit lines during the COVID-19 shock? And if so, why? For example, Sufi (2009) shows that profitable firms rely more on credit lines as high cash is critical to satisfying covenants. Unlike this paper, Sufi's study focuses on a period when credit was abundant. Berrospide & Meisenzahl (2015) show that firms draw down credit lines to mitigate liquidity shocks, and Ivashina & Scharfstein (2010) show that firms, during the financial crisis, drew down their credit lines for precautionary reasons, while Berrospide & Meisenzahl (2015) show that firms drew down mainly to support investments. More recently, Bosshardt & Kakhbod (2020) show that US firms drew down their credit lines for precautionary reasons in anticipation of liquidity shock with heterogeneous variations across different sectors. We build and extend this literature by employing a new measure of liquidity constraint and shed new light on firms' decisions to draw down credit lines during the COVID-19 shock. We use firms' drawdown size and credit line usage to represent firms' financing decisions. More specifically, the drawdown size is the ratio of the credit line drawdowns scaled by non-cash assets. In contrast, credit line usage is a variable between 0 and 1, showing the drawdown amount in proportion to the total committed credit lines. We use the indicator developed by Bosshardt & Kakhbod (2020):

$$\text{Distress}_t = \frac{\text{Short-term Debt}_t - \text{Cash \& Cash Equivalent}_t - \text{Net Income}_t}{\text{Total Assets}_t} \tag{4}$$

where higher (lower) Distress_t implies a tighter (looser) liquidity-based financial constraint reflecting capacity to meet current liabilities. We apply this measure of firms' distress to our firms before and after the start of the pandemic shock.

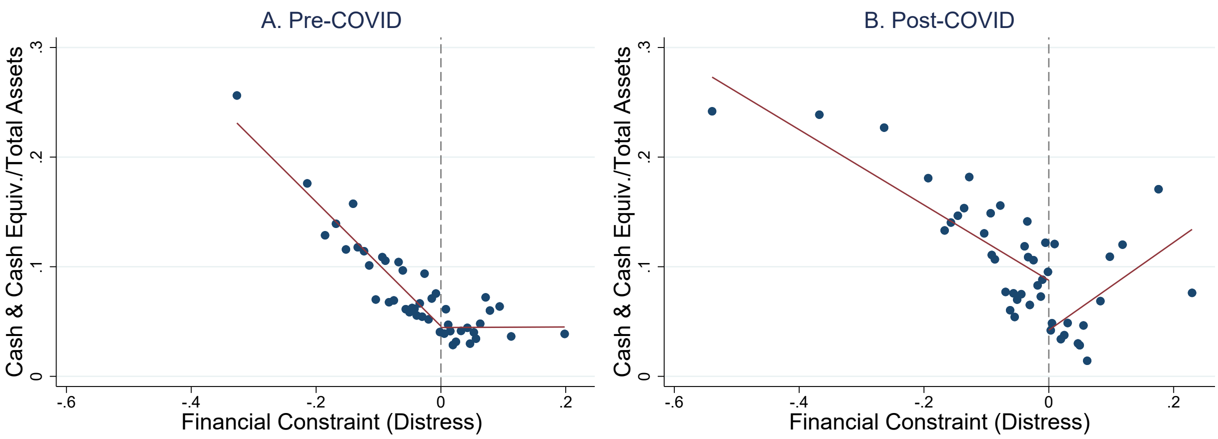


Figure 6. The diagram on the left shows the regression-discontinuity design (RID) of cash and cash equivalents against financial constraint (distress) before COVID. The horizontal axis shows the distress ratio, and the vertical axis shows the cash and cash equivalents relative to total assets. The diagram 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.

Figure (6) shows the relationship between firms' distress and cash and cash equivalent. We consider two periods: before the COVID-19 period and after. We note that in the pre-COVID-19 period, only financially constrained firms held higher cash provisions, but that changed in the post-COVID-19 period when financially constrained and unconstrained firms held higher liquidity provisions. We test for the relationship between distress and credit line draw-downs by including quarter dummies and using the following specification:

$$Drawdown_{i,t} = \alpha + \beta_1 Distress_{i,t} + \beta_2 Distress_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t} \tag{5}$$

where the notations and controls are defined earlier.

Table (4) shows the results. We test the association between firms' distress 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 (Panel B). Secondly, we note a significant positive association between firms' distress (cash holding) and credit line drawdowns in Panel B and the whole sample. Campello et al. (2011), for the financial crisis period and US firms, show a negative relationship between credit lines drawdowns and cash holdings and interpret it as a substitution effect between internal and external liquidity. We do not find it for European firms during the COVID-19 shock. We interpret the negative relationship between distress and credit line drawdowns as suggesting that firms with less stringent liquidity constraints used credit lines during the COVID-19 shock. In sum, firms with less stringent liquidity constraints drew down their credit lines and topped out cash holdings in 2020:Q2.

To shed further light on this result, we divide firms into three groups based on distress in Table (4). We use a 25%, 50% and 25% allocation as before. Moreover, we have tried other combinations, and the results we present in this section remain unchanged. Results are available upon request[10]. There is a negative association between firms' distress and credit line drawdowns in 2020:Q2. Firms with less stringent liquidity constraints drew down credit lines in 2020:Q2. This result contrasts with both Campello et al. (2011) and Sufi (2009).

In Figure (7), we show the change in cash holding in 2020:Q2 and Distress. Firms with the most remarkable change in cash holding were the ones within the Low Distress group. These results suggest that during the COVID-19 shock, firms with less stringent liquidity constraints drew-down credit lines and increased cash holdings. In the next section, we shall try to understand the reasons. In sum, we do not find a substitution effect as in Campello et al. (2011) for European firms during the COVID-19 shock, but instead, results in this and previous section seem to suggest that in 2020:Q2 a "panic borrowing" took place amongst Europen firms which led to the observed fly to liquidity. These are new results, which we will investigate further in the next section.

[10] In all these regressions, we have used the same controls as the ones reported in the previous sections.

	Drawdown Size			Credit Line Usage		
	(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)
$\text{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)
$\text{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)
$\text{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 4. **Drawdowns on Liquidity Distress**. This table shows the results of the baseline models in equation (5). 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 the usage of credit lines. 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*. 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) Medium Distress	(4) High Distress	(5) All Firms	(6) Low Distress	(7) Medium Distress	(8) High Distress
Distress_t	0.240***	0.368**	-0.038	0.830***	0.417***	1.347***	-0.916*	0.990***
	(0.047)	(0.156)	(0.151)	(0.109)	(0.133)	(0.428)	(0.470)	(0.307)
$\text{Distress}_t \times$2020:Q2	-0.188***	-0.360**	-0.133	0.119	-0.283*	-1.302***	0.189	0.524
	(0.052)	(0.158)	(0.403)	(0.254)	(0.148)	(0.434)	(1.252)	(0.713)
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	238	416	148	788	231	410	145
Adjusted R^2	0.047	0.076	0.021	0.383	0.024	0.085	0.052	0.186

Table 5. **Drawdowns on Distress by Firm Types**. This table shows the results of the baseline models in equation (5) 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 ndependent 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

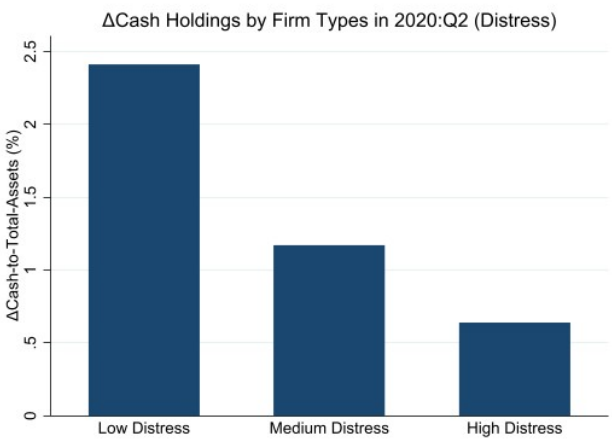


Figure 7. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current scale less the previous one, against different firm types based on financial constraint (distress). The horizontal axis shows three types of firms: Low Distress (25%), Medium Distress (50%) and High Distress (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.

3.4 Shortfall in Revenue and Access to Credit Lines

Why did less financially constrained firms to draw down credit lines in 2020:Q2? In this section, we attempt to answer this question. The previous literature suggests that profitable firms draw down credit lines, while non-profitable firms rely mainly on internal liquidity. We conjecture that firms with good solvency and liquidity positions expected a significant shortfall in revenue (or cash flow) and drew down their credit lines, topping up cash. A shortfall in revenue following the COVID-19 shock can seriously affect a firm's financing requirements as this increases firms' credit risk (for example, see Acharya & Steffen (2020*b*)). Therefore, the panic borrowing we showed could be the consequence of the expected shortfall in revenue. Differently from our study, we also explictly for this possibility and investigate it. We use cash flow as measured by the EBITDA, net income with interests, taxes, depreciation, and amortization. We include time and industry fixed effects:

$$\begin{aligned}\text{Drawdown}_{i,t} &= \beta_0 + \beta_1 \text{EBITDA}_{i,t} + \beta_2 \text{EBITDA}_{i,t} \times 2020\text{:Q2} + \\ &\quad \gamma X_{i,t} + \epsilon_{i,t}\end{aligned} \tag{6}$$

where *Drawdown* is a ratio with respect firms' non-cash 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 the non-cash assets, the natural logarithm of non-cash assets, the price-to-book ratio, and the leverage ratio. Time and industry fixed effects are included. We consider firms with at least one observation before and after 2020:Q2.[11]

We show the results using contemporaneous and lagged specifications in Table (6) and Table (7), respectively, where we also include three dummies, one for each quarter. We use all the firms in column (1), firms with low financial distress in column (2) and the ones with high financial distress in column (3). Sufi (2009) and Berrospide & Meisenzahl (2015) show that profitable firms (these papers use cash) draw down credit lines as these are likely to meet covenants imposed by banks. However, they use data from a period when credit is abundant. Acharya & Steffen (2020*b*) show that a shortfall in revenue can increase credit risk and a firm's financing requirements. Following Acharya et al. (2012), we expect the β_1 to be negative and significant, indicating a negative association between cash flow and credit line drawdowns. Cash flow at time $t-1$ has a significant and negative impact on credit lines draw down. Credit line usage results are summarized in columns (4) across (6). We note that cash holdings are only marginally significant in very few cases. Overall the results are similar with lag and contemporaneous specifications and support the assumption that, at the start of the pandemic shock, an unexpected fall in revenue drove firms with good liquidity (solvency) positions, to draw down credit lines. These results support the conjecture that the flight to liquidity across European firms during the COVID-19 shock was a "panic borrowing". Indeed, as we show in the next section, it was mainly a "panic borrowing" consequently an unexpected (largely unknown) event and the subsequent lockdown of a large part of the economies across Europe.

To further shed light on these results, in Table (8), we divided firms into Lower, Medium and High EBITDA. In 2020:Q2, the dummy coefficient is only significant for firms with lower EBITDA, and this coefficient carries a negative sign. Therefore, in 2020:Q2, firms whose cash flow was expected to be impacted by the COVID-19 shock drew down their credit lines to increase cash holding in response to an increase in aggregate risk. While these results are consistent with the "panic borrowing" status, they also point towards the possibility of an endogenous role of credit lines drawdowns. We shall address this possibility in the next section. Figure (8) shows, for the three groups, the change in cash holding between 2020:Q1 and 2020:Q2. The low EBITDA group shows the most considerable change in cash holding. The right diagram shows that low-risk firms (low solvency risk firms) experienced the most significant drop in EBITDA in 2020:Q2.

[11] Results not included in this paper show that, they remain consistent after accounting for survival bias particularly when a certain fraction of firms face bankruptcies. These results are available upon request

	Credit Line Drawdowns			Credit line Usage		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Firms	Low Distress	High Distress	All Firms	Low Distress	High Distress
	Panel A: 2020:Q1					
EBITDA_t	-0.198	-0.176	0.157	-0.993**	-0.959**	-0.081
	(0.143)	(0.149)	(0.617)	(0.410)	(0.422)	(1.888)
$\text{EBITDA}_t \times$2020:Q1	0.069	0.023	4.529	0.791	0.147	19.950
	(0.827)	(0.858)	(4.483)	(2.374)	(2.421)	(13.709)
Cash Holdings_t	0.033	0.033	0.033	0.281*	0.275	0.359
	(0.054)	(0.058)	(0.214)	(0.160)	(0.171)	(0.659)
Leverage_t	0.071***	0.077***	0.067	0.177**	0.215***	0.061
	(0.026)	(0.028)	(0.093)	(0.073)	(0.077)	(0.291)
$\log(\text{P/B})_t$	-0.005	-0.006	0.026	-0.018	-0.024	0.054
	(0.005)	(0.006)	(0.022)	(0.016)	(0.016)	(0.069)
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	0.022	0.022	0.088	0.028	0.030	0.170
	Panel B: 2020:Q2					
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
	Panel C: 2020:Q3					
EBITDA_t	-0.202	-0.160	-0.293	-0.930**	-0.826*	-1.311
	(0.144)	(0.149)	(0.671)	(0.414)	(0.421)	(2.074)
$\text{EBITDA}_t \times$2020:Q2	0.144	-0.599	2.572*	-1.188	-4.488**	7.329
	(0.600)	(0.714)	(1.508)	(1.699)	(1.985)	(4.656)
Cash Holdings_t	0.032	0.036	-0.037	0.280*	0.299*	0.127
	(0.053)	(0.058)	(0.213)	(0.160)	(0.170)	(0.661)
Leverage_t	0.072***	0.076***	0.106	0.175**	0.211***	0.176
	(0.026)	(0.028)	(0.094)	(0.073)	(0.077)	(0.298)
$\log(\text{P/B})_t$	-0.005	-0.006	0.033	-0.016	-0.021	0.078
	(0.005)	(0.006)	(0.022)	(0.015)	(0.016)	(0.069)
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	0.022	0.023	0.111	0.029	0.038	0.174

Table 6. **Drawdowns on EBITDA (Contemporaneous specification)** The table shows firms' reliance on credit lines (columns 1-3) and credits line usages (columns 3-6) where both contemporaneous and lagged specifications are included in Panels A and B, respectively. We use industry, firm, country and time fixed effects. The leverage covariate is the total leverage and log(P/B) is the natural logarithm of price-to-book ratio. 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Credit Line Drawdowns			Credit line Usage		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Firms	Low Distress	High Distress	All Firms	Low Distress	High Distress
	Panel A: 2020:Q1					
EBITDA_{t-1}	-0.447*	-0.575*	0.571	-1.978**	-4.367***	2.150
	(0.245)	(0.342)	(0.784)	(0.936)	(1.403)	(2.526)
$\text{EBITDA}_{t-1}\times$2020:Q1	-0.097	0.497	-4.070**	0.086	4.123**	-10.974*
	(0.414)	(0.499)	(1.991)	(1.573)	(2.054)	(6.316)
$\text{Cash Holdings}_{t-1}$	0.137**	0.108	0.112	0.396	0.401	0.497
	(0.070)	(0.078)	(0.181)	(0.268)	(0.330)	(0.585)
Leverage_{t-1}	0.040	0.026	0.089	0.185*	0.224*	0.159
	(0.027)	(0.028)	(0.089)	(0.101)	(0.114)	(0.286)
$\log(\text{P/B})_{t-1}$	0.003	0.003	0.019	-0.010	-0.003	0.007
	(0.006)	(0.007)	(0.018)	(0.025)	(0.029)	(0.064)
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	389	294	95	381	289	92
Adjusted R^2	0.060	0.031	0.129	0.033	0.059	0.173
	Panel B: 2020:Q2					
EBITDA_{t-1}	-0.416**	-0.227	-0.202	-1.732**	-2.214*	-0.149
	(0.211)	(0.277)	(0.742)	(0.805)	(1.160)	(2.340)
$\text{EBITDA}_{t-1}\times$2020:Q2	-0.915	-1.555**	3.175	-3.325	-5.100	12.341
	(0.620)	(0.772)	(3.228)	(2.348)	(3.188)	(10.041)
$\text{Cash Holdings}_{t-1}$	0.124*	0.102	0.130	0.357	0.396	0.609
	(0.069)	(0.078)	(0.195)	(0.266)	(0.331)	(0.625)
Leverage_{t-1}	0.042	0.031	0.045	0.193*	0.239**	0.018
	(0.027)	(0.028)	(0.091)	(0.101)	(0.115)	(0.291)
$\log(\text{P/B})_{t-1}$	0.004	0.003	0.021	-0.006	-0.011	0.015
	(0.006)	(0.006)	(0.019)	(0.024)	(0.028)	(0.064)
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	389	294	95	381	289	92
Adjusted R^2	0.065	0.042	0.091	0.038	0.054	0.155
	Panel C: 2020:Q3					
EBITDA_{t-1}	-0.588***	-0.342	-1.071	-2.425***	-2.590**	-1.846
	(0.226)	(0.289)	(1.007)	(0.858)	(1.213)	(3.239)
$\text{EBITDA}_{t-1}\times$2020:Q3	0.532	-0.142	2.244	2.316	-0.487	4.767
	(0.432)	(0.612)	(1.581)	(1.640)	(2.551)	(5.031)
$\text{Cash Holdings}_{t-1}$	0.138**	0.114	0.061	0.414	0.447	0.314
	(0.069)	(0.079)	(0.182)	(0.265)	(0.333)	(0.587)
Leverage_{t-1}	0.045*	0.026	0.113	0.207**	0.225*	0.187
	(0.027)	(0.028)	(0.096)	(0.102)	(0.115)	(0.305)
$\log(\text{P/B})_{t-1}$	0.002	0.002	0.025	-0.013	-0.015	0.033
	(0.006)	(0.006)	(0.018)	(0.024)	(0.028)	(0.064)
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	389	294	95	381	289	92
Adjusted R^2	0.064	0.028	0.104	0.038	0.045	0.148

Table 7. **Drawdowns on EBITDA (Lagged specification)** The table shows firms' reliance on credit lines (columns 1-3) and credits line usages (columns 3-6) where both contemporaneous and lagged specifications are included in Panels A and B, respectively. We use industry, firm, country and time fixed effects. The leverage covariate is the total leverage and log(P/B) is the natural logarithm of price-to-book ratio. 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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 8. **Drawdowns on EBITDA by firm types.** This table shows the results of the baseline models in equation (5) 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 ndependent 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

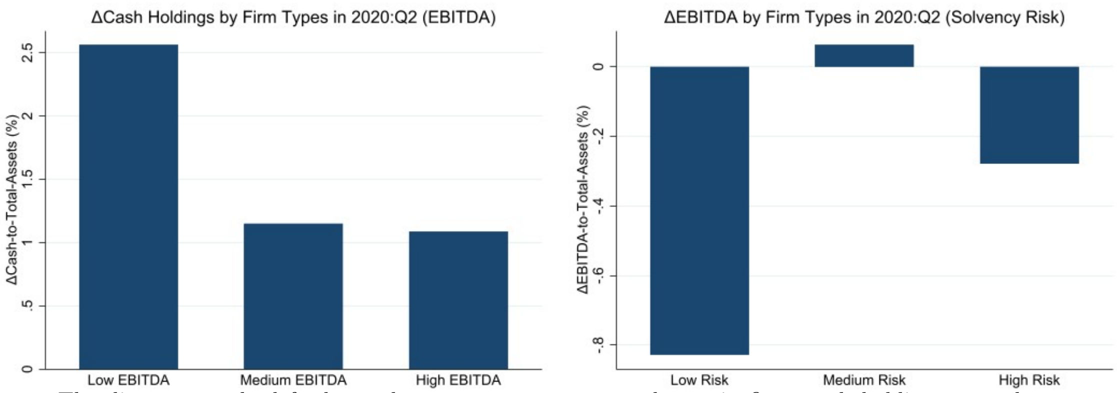


Figure 8. The diagram on the left shows the aggregate percentage change in firms cash holding to total assets ratio by the underlying earning status, low, medium and high, respectively, which illustrates firms within the lowest status increased their cash holding relatively twice the other groups between the 2020:Q1-Q2. The diagram on the right shows the aggregate percentage changes in the earnings between 2020:Q1-Q2 according to the firms underlying risk profiles.

3.5 Discontinuity Analysis

We discussed that the "panic borrowing" showed earlier may point towards endogeneity in how firms use credit lines. We have yet to be aware of empirical studies which have addressed this critical issue. This section uses a novel econometric approach to study this issue.

We use a quasi experimental analysis to investigate firms' decisions to access credit lines around a defined break-even earning neighbourhood using the following specification:

$$\text{Drawdown}_{i,t} = \beta_0 + \beta_1 D_{i,t}(\lambda) + \beta_2 D_{i,t}(\lambda) \times \text{2020:Q2} + \gamma X_{i,t} + \epsilon_{i,t} \quad (7)$$

where λ denotes the choice of neighbourhood bandwidth such that D_i is equal to a firm performance outcome within $[0, \lambda)$ bandwidth and zero otherwise.[12] The notations follow the exact definition in equation (6), and we consider firms with at least one observation before and after 2020:Q2. The identification exploits a subsample of the firm-level data within the bandwidth to examine a discontinuity across credit line drawdown decisions within a neighbourhood. Performance outcomes across firms within the neighbourhood provide a quasi-randomisation experiment as realisations just above or below the zero thresholds drive firms' decisions to draw down credit lines. We expect that firms with performance just above the zero thresholds tend to behave differently from those with realisations just below the threshold.

The results are presented in Table (9), where we consider five bandwidths between 0.25-1.25 (columns (1) to (10)) multiplied by the EBITDA standard deviation. Take columns (1), (3), (5), (7), and (9) as an example. The coefficients on the dummy 2020Q2 are highly significant and negative for these values. They also decline in size from -1.071 to -0.722, that is, a 1.071 to 0.722 percentage point decrease in credit lines draw down to total assets ratio in response to a one percentage point increase in EBITDA-to-total assets ratio. Firms with marginally positive performance rely less on credit lines. Their performance and expected revenue, as measured by EBITDA, are essential in explaining decisions to use credit lines during the COVID-19 shock. These results confirm that during the pandemic shock, firms exhibited a shift in their drawdown decisions due to a shortfall in revenue. However, these results contrast with Sufi (2009) and Campello et al. (2011), who find that more profitable firms draw down credit lines. The panic borrowing is quite robust and seems to be driven by a shortfall in firms' revenue.[13]

[12]We use set a range of values for the bandwidth as in Chava & Roberts (2008) and Hoxby (2000). These papers provide a comprehensive discussion about the choice of bandwidth.

[13]Appendix (D) shows an alternative design of regression discontinuity in which we can have similar evidence with the one in Table (9).

Dependent Variable:	Drawdown Size									
	(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$_t$×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 9. **Regression Discontinuity Design on Drawdowns**. This table shows the credit line drawdown on the revenue within various groups based on free cash flow. 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, 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 subsamples based on the performance just below the threshold. The rest columns use subsamples 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 European firms, Financial Constraints and 2008-2012 Crises

Is the "panic borrowing" unique to the pandemic crisis? Answering this question is important to understand if the type of shock leading to an increase in aggregate risk matters to understand firms' preference for cash and, therefore, liquidity risk management. To address this question, we compare the impact of the COVID-19 crisis on firms' decisions to access internal and external funding with that of the 2008 - 2012 financial and European crises. Of course, these two shocks are very different as the former originated in the financial market and affected the banking system, while the latter did not. There is a large amount of literature documenting the impact of the 2008 financial crisis on US corporate decisions, particularly on the relationship between cash holdings (cash) and financial constraints. Our paper also speaks to this part of the literature but focuses mainly on credit line drawdowns.

4.1 Previous Crises

4.1.1 2008 Financial Crisis

In Table (10) to Table (12), we use solvency and liquidity constraints and study if European firms' hit by the 2008 finacial crisis draw down credit lines. We show the results for 2008:Q2-2008:Q4.

In general, if we consider all the firms, there is a negative association between firms' solvency (Table (10)), liquidity (Table (11)) risk, and credit lines drawdown. Furthermore, There is weak evidence that the financial crisis's shock is associated with firms' decisions to draw down credit lines. For all the firms, there is evidence that all European firms reduced access to their credit lines regardless of their solvency or liquidity status. In a nutshell, there is weak evidence that the 2008 financial crisis, differently than the US, acted as a detonator leading to a dash for cash.[14]

4.1.2 2012 European Crisis

We now turn to the European crisis. This comparison should help us understand if there are any significant differences in corporate decisions under these two very different crises or if the COVID-19 crisis introduced a new approach to corporate decisions. We show the results in Table (13) to Table (15).

Firms' solvency risk is not always significant and is negatively associated with their decisions to draw down credit lines. The empirical evidence is also weak when liquidity constraints are introduced (Table (14)) and also for firms facing a shortfall in revenue (Table (15)). Overall, there is weak evidence that the 2012 European crisis acted as a detonator for firms to dash for cash. The results showed that the COVID-19 period is unique to that type of shock. European firms drew down their credit lines for precautionary motives driven by a "panic borrowing".[15] Finally, our results contrast with the extensive literature on financial constraints during the 2008 financial crisis and the dash for cash of US firms (Sufi 2009).

[14]We also introduced Cash Holdings in Table (10. Cash holding is generally significant and positive for RID but insignificant and negative for liquidity distress. In a way, cash holdings accumulation does not seem to matter for European firms during the financial and European crises.) to Table (12) and coefficients are all generally highly significant, but while with RID, they carry a positive sign, they become negative in the case of Distress and EBITDA.

[15]We also include Cash Holdings in Table (13) to Table (15) and while the coefficients are generally highly significant, once again, are positive for RID and negative for Distress and EBITDA.

	Drawdown Size				Credit Line Usage			
	(1) All Firms	(2) Low Risk	(3) Medium Risk	(4) High Risk	(5) All Firms	(6) Low Risk	(7) Medium Risk	(8) High Risk
Panel A: 2008:Q2								
RID_{t-1}	-0.072***	-0.094**	-0.059	-0.080	-0.151***	-0.263***	-0.358***	-0.086
	(0.014)	(0.045)	(0.042)	(0.089)	(0.032)	(0.083)	(0.132)	(0.236)
$\mathrm{RID}_{t-1}\times$2008:Q2	-0.030	-0.238	0.066	-0.436**	-0.127	-0.555	0.298	-0.737
	(0.051)	(0.408)	(0.132)	(0.175)	(0.118)	(0.745)	(0.419)	(0.463)
Observations	498	106	254	138	500	107	255	138
Adjusted R^2	0.203	0.155	0.161	0.346	0.209	0.248	0.195	0.308
Panel B: 2008:Q3								
RID_{t-1}	-0.072***	-0.095**	-0.056	-0.095	-0.154***	-0.266***	-0.348**	-0.116
	(0.014)	(0.045)	(0.043)	(0.091)	(0.032)	(0.082)	(0.135)	(0.238)
$\mathrm{RID}_{t-1}\times$2008:Q3	-0.014	-0.168	0.013	-0.113	-0.048	-0.411	0.113	-0.100
	(0.046)	(0.285)	(0.109)	(0.174)	(0.107)	(0.519)	(0.345)	(0.456)
Observations	498	106	254	138	500	107	255	138
Adjusted R^2	0.202	0.155	0.160	0.313	0.208	0.249	0.194	0.293
Panel C: 2008:Q4								
RID_{t-1}	-0.076***	-0.112**	-0.051	-0.102	-0.163***	-0.303***	-0.284**	-0.120
	(0.014)	(0.046)	(0.042)	(0.091)	(0.033)	(0.084)	(0.131)	(0.238)
$\mathrm{RID}_{t-1}\times$2008:Q4	0.027	0.149	-0.042	-0.091	0.071	0.308	-0.709	0.042
	(0.037)	(0.130)	(0.142)	(0.187)	(0.086)	(0.237)	(0.447)	(0.488)
Observations	498	106	254	138	500	107	255	138
Adjusted R^2	0.203	0.165	0.161	0.312	0.209	0.259	0.202	0.293

Table 10. **Drawdowns and Solvency Risk in 2008 Financial Crisis**. This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the RID ratio and *2008:Q2*, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the RID ratio and *2008:Q3*, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the RID ratio and *2008:Q4*, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Risk Firms*). 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) Medium Distress	(4) High Distress	(5) All Firms	(6) Low Distress	(7) Medium Distress	(8) High Distress
Panel A: 2008:Q2								
Distress_t	-0.041	0.112	-0.310**	-0.016	-0.123	0.414*	-0.158	-0.253
	(0.036)	(0.082)	(0.154)	(0.079)	(0.091)	(0.229)	(0.384)	(0.190)
$\text{Distress}_t \times$2008:Q2	0.001	-0.057	0.543	-0.299	-0.054	-0.248	0.542	-0.498
	(0.070)	(0.096)	(0.595)	(0.288)	(0.176)	(0.269)	(1.484)	(0.696)
Observations	916	250	450	215	917	250	451	215
Adjusted R^2	0.081	0.119	0.063	0.173	0.133	0.122	0.097	0.232
Panel B: 2008:Q3								
Distress_t	-0.037	0.113	-0.270*	-0.043	-0.117	0.409*	-0.199	-0.286
	(0.036)	(0.082)	(0.156)	(0.080)	(0.091)	(0.228)	(0.388)	(0.194)
$\text{Distress}_t \times$2008:Q3	-0.059	-0.082	-0.211	0.069	-0.128	-0.263	0.950	0.003
	(0.067)	(0.089)	(0.529)	(0.234)	(0.169)	(0.248)	(1.316)	(0.566)
Observations	916	250	450	215	917	250	451	215
Adjusted R^2	0.082	0.121	0.062	0.169	0.133	0.123	0.098	0.230
Panel C: 2008:Q4								
Distress_t	-0.058	0.082	-0.335**	-0.140	-0.168*	0.255	-0.467	-0.413*
	(0.038)	(0.084)	(0.168)	(0.087)	(0.096)	(0.233)	(0.418)	(0.212)
$\text{Distress}_t \times$2008:Q4	0.066	0.078	0.221	0.404**	0.165	0.430**	1.448*	0.492
	(0.048)	(0.067)	(0.317)	(0.167)	(0.120)	(0.187)	(0.787)	(0.408)
Observations	916	250	450	215	917	250	451	215
Adjusted R^2	0.083	0.123	0.062	0.193	0.134	0.138	0.104	0.236

Table 11. **Drawdowns and Liquidity Distress in 2008 Financial Crisis**. This table shows the results of the baseline models in equation (5) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the liquidity distress and *2008:Q2*, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the distress and *2008:Q3*, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the distress and *2008:Q4*, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Distress Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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
Panel A: 2008:Q2								
EBITDA$_t$	-0.224**	-0.373	-0.803	-0.041	-0.409	-1.123	-0.735	0.831
	(0.096)	(0.320)	(0.573)	(0.170)	(0.261)	(0.830)	(1.451)	(0.587)
EBITDA$_t$×2008:Q2	0.140	-0.032	-1.342	0.176	0.304	0.726	-2.981	0.415
	(0.342)	(0.998)	(2.043)	(0.493)	(0.925)	(2.602)	(5.173)	(1.705)
Observations	818	205	427	185	819	206	427	185
Adjusted R^2	0.132	0.134	0.225	0.097	0.133	0.130	0.270	0.054
Panel B: 2008:Q3								
EBITDA$_t$	-0.220**	-0.422	-0.828	-0.042	-0.427	-1.189	-0.948	0.900
	(0.096)	(0.318)	(0.574)	(0.171)	(0.260)	(0.828)	(1.453)	(0.592)
EBITDA$_t$×2008:Q3	0.078	1.715	-0.966	0.159	0.646	3.391	0.410	-0.545
	(0.352)	(1.411)	(2.148)	(0.531)	(0.953)	(3.686)	(5.440)	(1.836)
Observations	818	205	427	185	819	206	427	185
Adjusted R^2	0.132	0.141	0.225	0.096	0.133	0.133	0.269	0.055
Panel C: 2008:Q4								
EBITDA$_t$	-0.253**	-0.604	-0.979	0.011	-0.592*	-1.666*	-0.850	0.396
	(0.115)	(0.379)	(0.631)	(0.209)	(0.311)	(0.988)	(1.597)	(0.720)
EBITDA$_t$×2008:Q4	0.109	0.579	0.431	-0.100	0.577	1.418	-0.341	1.142
	(0.190)	(0.525)	(1.371)	(0.311)	(0.513)	(1.364)	(3.471)	(1.073)
Observations	818	205	427	185	819	206	427	185
Adjusted R^2	0.132	0.140	0.225	0.096	0.134	0.135	0.269	0.061

Table 12. **Drawdowns and Cash Flow in 2008 Financial Crisis**. This table shows the results of the baseline models in equation (6) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the EBITDA and *2008:Q2*, time dummies indicating the second quarter in 2008. Panel B shows the interactions between the EBITDA and *2008:Q3*, time dummies indicating the third quarter in 2008. Panel C shows the interactions between the EBITDA and *2008:Q4*, time dummies indicating the fourth quarter in 2008. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-, Medium-*, and *High-EBITDA Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Drawdown Size				Credit Line Usage			
	(1) All Firms	(2) Low Risk	(3) Medium Risk	(4) High Risk	(5) All Firms	(6) Low Risk	(7) Medium Risk	(8) High Risk
Panel A: 2012:Q2								
RID_{t-1}	0.006**	0.004	-0.082**	-0.008	0.012*	0.007	-0.057	0.037
	(0.003)	(0.003)	(0.037)	(0.047)	(0.007)	(0.008)	(0.090)	(0.115)
$\text{RID}_{t-1}\times$2012:Q2	-0.003	0.003	0.091	0.239	-0.006	0.002	0.173	0.404
	(0.011)	(0.014)	(0.172)	(0.173)	(0.027)	(0.032)	(0.417)	(0.422)
Observations	1493	450	657	385	1497	452	658	386
Adjusted R^2	0.220	0.300	0.273	0.092	0.149	0.247	0.161	0.127
Panel B: 2012:Q3								
RID_{t-1}	0.006**	0.005	-0.086**	0.011	0.011	0.008	-0.074	0.036
	(0.003)	(0.004)	(0.037)	(0.047)	(0.007)	(0.008)	(0.090)	(0.114)
$\text{RID}_{t-1}\times$2012:Q3	-0.002	-0.001	0.166	-0.067	0.007	-0.006	0.572	0.418
	(0.009)	(0.011)	(0.165)	(0.170)	(0.021)	(0.024)	(0.398)	(0.415)
Observations	1493	450	657	385	1497	452	658	386
Adjusted R^2	0.220	0.300	0.274	0.088	0.149	0.247	0.163	0.127
Panel C: 2012:Q4								
RID_{t-1}	0.006*	0.004	-0.077**	0.009	0.011	0.004	-0.035	0.051
	(0.003)	(0.004)	(0.038)	(0.047)	(0.007)	(0.008)	(0.092)	(0.114)
$\text{RID}_{t-1}\times$2012:Q4	0.003	0.007	-0.024	-0.021	0.009	0.029	-0.241	0.158
	(0.009)	(0.010)	(0.141)	(0.149)	(0.021)	(0.023)	(0.340)	(0.365)
Observations	1493	450	657	385	1497	452	658	386
Adjusted R^2	0.220	0.300	0.273	0.087	0.149	0.249	0.161	0.125

Table 13. **Drawdowns and Solvency Risk in 2012 European Crisis**. This table shows the results of the baseline models in equation (2) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by non-cash assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the RID ratio and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the RID ratio and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the RID ratio and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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) Medium Distress	(4) High Distress	(5) All Firms	(6) Low Distress	(7) Medium Distress	(8) High Distress
Panel A: 2012:Q2								
Distress_t	0.072***	0.022	0.116*	0.066*	0.089**	0.128	0.504***	0.031
	(0.015)	(0.032)	(0.065)	(0.035)	(0.035)	(0.083)	(0.160)	(0.073)
$\text{Distress}_t \times$2012:Q2	-0.039	-0.015	0.022	-0.207	-0.084	0.124	-0.772	-0.332
	(0.050)	(0.088)	(0.316)	(0.158)	(0.117)	(0.227)	(0.782)	(0.326)
Observations	3232	814	1535	883	3234	814	1537	883
Adjusted R^2	0.110	0.037	0.115	0.120	0.116	0.089	0.086	0.164
Panel B: 2012:Q3								
Distress_t	0.071***	0.023	0.096	0.063*	0.083**	0.132	0.446***	0.022
	(0.015)	(0.032)	(0.065)	(0.035)	(0.035)	(0.083)	(0.160)	(0.073)
$\text{Distress}_t \times$2012:Q3	-0.014	-0.037	0.527*	-0.135	0.074	0.005	0.725	-0.149
	(0.045)	(0.063)	(0.292)	(0.158)	(0.106)	(0.162)	(0.724)	(0.327)
Observations	3232	814	1535	883	3234	814	1537	883
Adjusted R^2	0.110	0.038	0.116	0.119	0.116	0.089	0.086	0.163
Panel C: 2012:Q4								
Distress_t	0.069***	0.014	0.099	0.055	0.062*	0.099	0.406**	-0.019
	(0.015)	(0.033)	(0.066)	(0.036)	(0.036)	(0.084)	(0.164)	(0.075)
$\text{Distress}_t \times$2012:Q4	0.016	0.063	0.179	0.018	0.252***	0.299**	0.680	0.311
	(0.034)	(0.054)	(0.192)	(0.107)	(0.080)	(0.139)	(0.476)	(0.220)
Observations	3232	814	1535	883	3234	814	1537	883
Adjusted R^2	0.110	0.039	0.115	0.118	0.119	0.094	0.086	0.165

Table 14. **Drawdowns and Liquidity Distress in 2012 European Crisis**. This table shows the results of the baseline models in equation (5) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the liquidity distress and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the distress and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the distress and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-*, *Medium-*, and *High-Distress Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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
Panel A: 2012:Q2								
EBITDA_t	-0.102**	-0.129*	-0.125	-0.018	-0.188*	-0.025	0.376	-0.484
	(0.040)	(0.071)	(0.352)	(0.121)	(0.104)	(0.189)	(0.883)	(0.357)
$\text{EBITDA}_t \times$2012:Q2	-0.005	-0.003	-0.450	0.067	0.336	-0.384	2.498	-1.109
	(0.261)	(0.381)	(1.874)	(0.929)	(0.682)	(1.015)	(4.704)	(2.744)
Observations	2936	772	1469	695	2938	772	1471	695
Adjusted R^2	0.164	0.259	0.152	0.161	0.109	0.187	0.095	0.102
Panel B: 2012:Q3								
EBITDA_t	-0.089**	-0.110	-0.155	-0.026	-0.129	0.024	0.258	-0.520
	(0.040)	(0.072)	(0.354)	(0.122)	(0.105)	(0.191)	(0.888)	(0.359)
$\text{EBITDA}_t \times$2012:Q3	-0.309*	-0.368	0.374	0.341	-1.262***	-1.125*	4.581	0.936
	(0.181)	(0.237)	(1.630)	(0.584)	(0.472)	(0.630)	(4.091)	(1.725)
Observations	2936	772	1469	695	2938	772	1471	695
Adjusted R^2	0.165	0.262	0.152	0.162	0.111	0.191	0.096	0.102
Panel C: 2012:Q4								
EBITDA_t	-0.116***	-0.153**	-0.291	0.016	-0.179	-0.139	0.212	-0.406
	(0.042)	(0.074)	(0.366)	(0.125)	(0.109)	(0.198)	(0.918)	(0.369)
$\text{EBITDA}_t \times$2012:Q4	0.125	0.191	1.414	-0.373	-0.026	0.845*	2.255	-0.985
	(0.119)	(0.182)	(1.083)	(0.365)	(0.309)	(0.483)	(2.721)	(1.078)
Observations	2936	772	1469	695	2938	772	1471	695
Adjusted R^2	0.165	0.260	0.153	0.163	0.109	0.191	0.096	0.103

Table 15. **Drawdowns and Cash Flow in 2012 European Crisis**. This table shows the results of the baseline models in equation (6) with different interactions and within different subsamples. In columns (1) through (4), the dependent variables are credit line drawdowns scaled by total assets. In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A shows the baseline models given the interactions between the EBITDA and *2012:Q2*, time dummies indicating the second quarter in 2012. Panel B shows the interactions between the EBITDA and *2012:Q3*, time dummies indicating the third quarter in 2012. Panel C shows the interactions between the EBITDA and *2012:Q4*, time dummies indicating the fourth quarter in 2012. Columns (1) and (5) show the baseline models within the whole sample (*All Firms*). The rest columns show three sub-samples (*Low-, Medium-*, and *High-EBITDA Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Lockdown Policy and Credit Lines

We showed that during the COVID-19 shock, European firms went into a "panic borrowing" essentially driven by an unexpectedly sharp fall in revenue and firms with good solvency and liquidity risk drew down their credit lines and topped up their cash holdings provisions. We also showed that this result was essentially a unique feature of the COVID-19 crisis and had no precedent with other crises in Europe (the 2008 financial crisis and the 2012 European crisis). In the following sections, we study the differential effect of COVID-19 on European firms' decisions to access credit lines. We investigate if European firms in different countries, hit differently by the COVID-19 shock, drew down their credit lines. We consider the country's level of COVID-19 infection data and the country's specific social distancing policy (less or more stringent) to define country flexibility. The idea of doing this is twofold. First, it will allow us to directly use the information from the COVID-19 shock (i.e. infection rates across countries) to study if the "panic borrowing" is a consequence of the stringent policy measures. Second, It also presents the opportunity to run additional robustness tests to support the empirical results presented in the previous section and mitigate potential endogeneity issues. We measure firms' impact of COVID-19 in two different ways. First, we follow Campello et al. (2020) and define high (low) COVID-19 impact within a specific country (we use four countries: Italy, Germany, Spain and France). We also use an alternative indicator as a proxy for social distancing strictness across European countries: the Oxford Stringency Index. A higher value of this index implies a stricter social distancing policy in that country.

4.2.1 Infection Rates, Mobility Policy and Credit Lines Drawdowns

We use Equation (8) below to study the relationship between infection rates (mobility policy) and firms' credit lines draw downs.

$$\begin{aligned} Drawdown_{i,t} &= \alpha + \beta_1 COVID\ Impact_{i,t} + \beta_2 (COVID\ Impact_{i,t} \times 2020{:}Q2) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{8}$$

where $Drawdown_{i,t}$ denotes: 1) credit line drawdowns divided by total assets, and 2) credit line usage. $COVID\ Impact_{i,t}$ is once 1). $High\ COVID\ Exposure_{i,t}$, a dummy equal to 1 each quarter the country is in the top 50% of the number of confirmed COVID cases per million and 0 elsewhere (Campello et al. 2020); 2) We also use $\log(Stringency)$, the logarithm of the Stringency Index which records the strictness of "lockdown style" policies. Higher Stringency Index restricts people's access to some jobs (Ritchie et al. 2020). *2020:Q2* is a time dummy which denotes the period of the shock. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of the price-to-book ratio. Industry fixed effect is included. The regression results of Equation (8) are documented in Table (16).

Table (16) shows that, generally, firms reduced access to credit lines during the whole sample period but increased reliance on credit lines in 2020Q2. Our results using the Stringency Index are even more supportive and show that more stringent social distancing rules lead to higher drawdowns. In a nutshell, at the peak of the COVID-19 shock, European firms facing a shortfall in revenue due to the unexpected lockdowns across Europe went into a "panic borrowing" status. They dashed for cash by drawing down their credit lines and accumulating cash. That is, the panic borrowing in Europe is driven by the unexpected shock introduced by the lockdown policies across Europe. Our results suggest that lockdown policies have introduced a new type of risk for firms' corporate liquidity risk management. This novel result is significant for future theoretical models on liquidity risk management as one would need to account for a run on credit lines, subsequently, a government policy (lockdown), which triggers cash accumulation. In a nutshell, these results in this and previous sections point towards an endogenous role of credit lines in liquidity risk management.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High COVID Exposure	-0.066***	-0.078***			-0.225***	-0.294***		
	(0.013)	(0.015)			(0.043)	(0.049)		
High COVID Exposure×2020:Q2		0.022				0.130***		
		(0.015)				(0.049)		
log(Stringency)			0.037**	0.045**			0.161***	0.183***
			(0.019)	(0.019)			(0.060)	(0.061)
log(Stringency)×2020:Q2				0.007**				0.020*
				(0.003)				(0.010)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	211	211	211	211	206	206	206	206
R^2	0.186	0.195	0.101	0.122	0.194	0.223	0.110	0.127

Table 16. **The impact of COVID-19 on Credit Line Drawdowns During the COVID-19 Shock**. This table presents the regression results of Equation (8). The dependent variable is $Drawdown_{i,t}$ which contains either credit line drawdown to total assets or the utilization of credit lines. $COVID\ Exposure_{i,t}$ represents two variables which are $High\ COVID\ Exposure_{i,t}$, a dummy equal to 1 that for each quarter the country belongs to the top 50% of the number of confirmed COVID cases per million and 0 elsewhere (Campello et al. 2020); 2) log(*Stringency*), the logarithm of the Stringency Index which records the strictness of 'lockdown style' policies that primarily restrict people's behaviour (Ritchie et al. 2020). *2020:Q2* is a time dummy which denotes the period of the shock. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of price-to-book ratio. Industry fixed effect is included. We show robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2 Social Distancing Policies Across European Countries

Given that European countries have implemented different mobility policies during the COVID-19 lockdowns, we want to condition the previous tests on the country's exposure to the spread of the virus and the strictness of social distancing policies. We study the relationship between social distancing rules across different countries and firms' decisions to draw down credit lines. Is there any significant difference amongst the social distancing policies adopted within Europe, which can help us to understand why firms drew down their credit lines and piled up cash? Figure (9) show the strictness of social distancing rules as measured by the Stringency Index across the four largest European economies. Italy, overall, experienced the most stringent mobility rule, followed by Germany. In this section, we investigate if the different stringent policy rules help us to understand firms' decisions to draw down credit lines.

We construct a specification to investigate the relationship between credit line drawdowns and the strictness of lockdown policies across countries as follows:

$$\begin{aligned} \mathit{Drawdown}_{i,t} &= \alpha + \beta_1 \mathit{log(Stringency)}_{i,t} + \beta_2 (\mathit{log(Stringency)}_{i,t} \times \mathit{Country}_i) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{9}$$

where $Drawdown_{i,t}$ has same definition as previous specifications. $\log(\mathit{Stringency})_{i,t}$ indicates the logarithm of the Stringency Index which records the strictness of 'lockdown style' policies. $\mathit{Country}_i$ is an indicator of different countries including Italy, Germany, France, and Spain. The controls have same definitions as previous specifications. Table (17) reports the regression results of Equation (9).

The relationship between the stringency index and credit lines draw down is positive and significant across all four countries. However, the impact of the social distancing policies on credit lines draw down is different across countries. For example, it is larger for Italy than Spain. Results in Table 19, although not conclusive, point in the direction that the different lockdown measures used across European countries produced a different impact on firms' decisions to draw down credit lines. Therefore, although the "panic borrowing" has the same origin across Europe (i.e. lockdown policies), it impacted firms' decisions to draw down credit lines differently.[16] These results have important policy implications as lockdown policies can generate negative externalities for firms and unexpectedly fly to liquidity.[17]

[16] We have also considered different quarters in our analysis.

[17] Credit line drawdowns also have serious implications for banks' liquidity management since banks commit them. Firms, as we showed, rely on them as insurance, especially in bad states. Our results suggest that country flexibility is important, although more work is necessary.

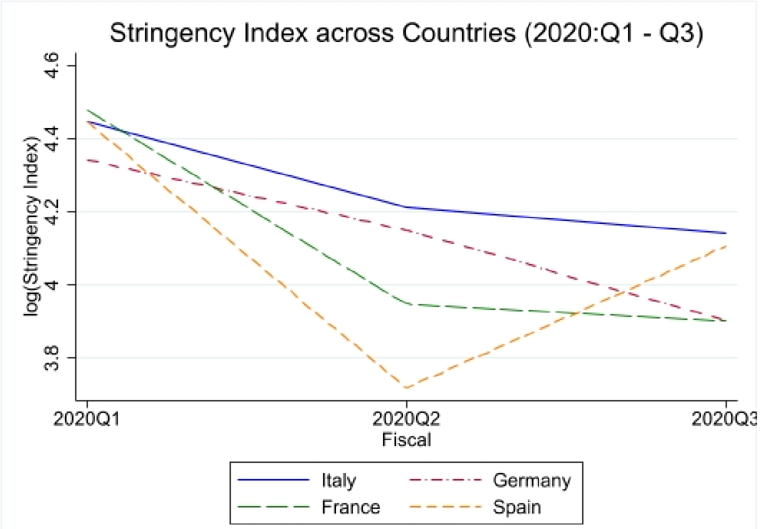


Figure 9. This diagram shows the strictness of lockdown policy across main European countries. The horizontal axis shows the three quarters when the COVID-19 pandemic burst. The vertical axis shows the logarithm of the Stringency Index which measures the strictness of 'lockdown style' policies.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Stringency)	0.023	0.037*	0.034*	0.038**	0.126**	0.130**	0.151**	0.161***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.061)	(0.061)	(0.060)	(0.060)
log(Stringency)×Italy	0.018***				0.045**			
	(0.006)				(0.020)			
log(Stringency)×Germany		0.000				0.030**		
		(0.004)				(0.013)		
log(Stringency)×France			0.014**				0.041**	
			(0.006)				(0.019)	
log(Stringency)×Spain				0.012**				0.014
				(0.006)				(0.020)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	211	211	211	211	206	206	206	206
R^2	0.140	0.101	0.125	0.120	0.134	0.133	0.131	0.112

Table 17. **The impact of COVID-19 on Credit Line Drawdowns (Countries).** This table shows the regression results of Eq. (9). The dependent variable is $Drawdown_{i,t}$ which contains either credit line drawdowns to total assets or the utilization of credit lines. log(*Stringency*) is the logarithm of the Stringency Index which records the strictness of 'lockdown policies (Ritchie et al. 2020). $Country_i$ is a set of dummies indicating European countries such as Italy, Germany, France, and Spain. Control variables include the leverage (total debt divided by total assets), the logarithm of total assets, the undrawn credit lines divided by total assets, and the logarithm of price-to-book ratio. Industry fixed effect is included. We report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Industrial Exposure to COVID-19

We showed that the economic shutdown of a large part of European economies following the COVID-19 shock led to a "panic borrowing" and cash accumulation. We also showed that the panic borrowing was driven by an unexpected shortfall in firms' revenue, which differed across countries. In the following sections, we extend our analysis and consider a novel type of flexibility, work flexibility or the capacity to perform a job from home, to shed further light on previous results. In sum, we introduce a new and additional dimension, work flexibility, when studying firms' liquidity risk management during COVID-19. Bosshardt & Kakhbod (2020) showed that the economic shutdown motivated firms to draw down their credit lines for a precautionary reason but that firms less exposed to the COVID-19 shock used, in part, some of the cash from drawdowns to support investments. Differently from Bosshardt & Kakhbod (2020), we study the impact of the COVID-19 shock across industries based on their ability to perform jobs remotely (work flexibility). We also extend that study to consider country flexibility, which means we consider social distancing policies within a specific country and across countries. The idiosyncratic effect of COVID-19 across different industries and countries is crucial as it helps to inform policymakers about policy responses to help the economy. As far as we know, this is the first paper to investigate this issue and directly link firms' idiosyncratic risk (i.e. work and country flexibility), credit lines drawdowns and corporate liquidity management.

We follow the survey developed by Dingel & Neiman (2020) conducted on a range of 1,000 occupations in the United States, investigating how many can be conducted from home. The finding highlights the impact of "social distancing" on the risk of exposure to COVID-19 across industries. According to this finding, constructing a 2-digit sector classification code provides a benchmark to identify the relative ability of labour to carry out their occupational commitments across industries. For instance, for professionals, scientific, and technical services, the estimated impact is 0.8, indicating that most occupations under this classification are relatively less affected by the social distancing policy. In contrast, accommodation and food services are more affected, with the estimated exposure equal to 0.04. We define the weight of jobs that can be done from home by:

$$\textit{Exposure} \quad = \quad 1 - \textit{Job Done at Home}$$

where *Exposure* shows the effect of the pandemic on an industry as expressed by the labour drivers. A higher exposure value implies a lower ability of occupational capacities to be fulfilled while impacted by the pandemic. As *Job Done at Home* is within an interval between 0 and 1, *Exposure* is also located in the same range.

While the framework developed by Dingel & Neiman (2020) uses the North American Industry Classification System (NAICS), in our 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,[18] 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 (18) shows the industrial exposure to COVID-19 within two industrial levels. In Figure (10), we show firms' access to their credit lines between 2020Q1 and 2020Q2. Energy, Technology, Real Estate and Materials are the ones that withdrew their credit lines during the pandemic shock.

The upper panel of Table (18) shows the main sectors of the industries. Consider Industrials (0.651) as an example. This contains not only Industrial Intermediate Products (0.78) but also Industrial Support Services (0.2). However, all the industries have more than half of the jobs affected by the pandemic, except Communications. If we define the sector which scores larger than 0.7 as an

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

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 18. **Industrial Exposure at COVID-19**. This table reports 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.

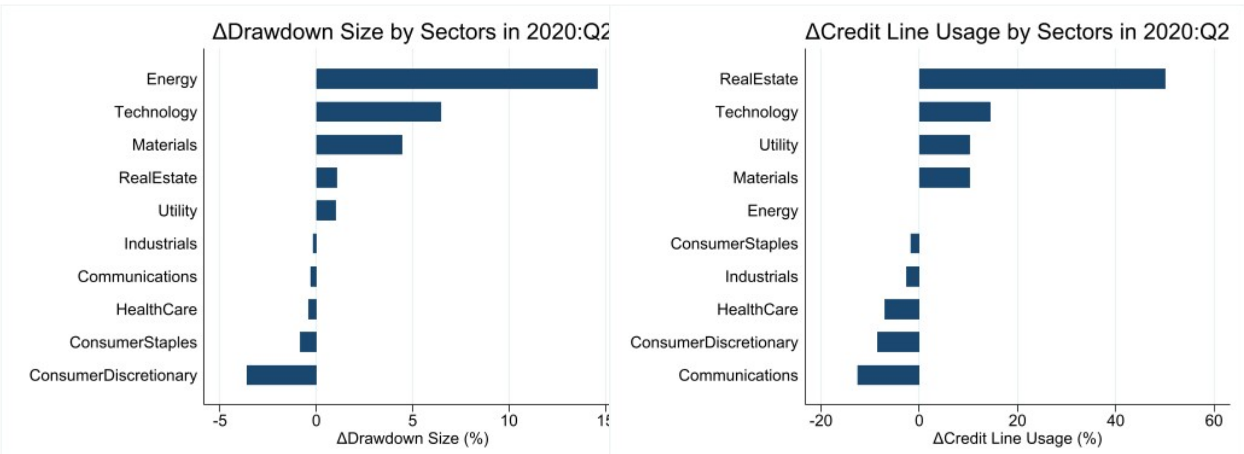


Figure 10. The diagram on the left shows the absolute difference in drawdowns between 2020:Q1-Q2 as a percentage of firms' total assets, whilst the diagram on the right shows firms' credit line utilization difference over the same time period, as a percentage of the firms' total assets.

exposed one, then Materials, Health Care, Consumer Discretionary, and Energy are *exposed* sectors. On the contrary, sectors which scores less than 0.3 are *unexposed* ones. Communications is the only *unexposed* sector. Using the same approach to the level-3 industry groups in the lower panel of Table (18), there are 35 *exposed* and 10 *unexposed* industry groups in total. *Exposed* groups including Retail-Consumer Staples, Retail-Discretionary, E-Commerce Discretionary, Engineering & Construction, Transportation & Logistics, Home Construction, Software, Transportation Equipment, Machinery, Aerospace & Defence, Chemicals, Electrical Equipment, Beverages, Technology Hardware, Steel, Medical Equipment & Devices, Containers & Packaging, Apparel & Textile Products, Biotech & Pharma, Industrial Intermediate Products, Diversified Industrials, Home & Office Products, Forestry, Paper & Wood Products, Semiconductors, Automotive, Household Products, Leisure Products, Construction Materials, Tobacco & Cannabis, Health Care Facilities & Services, Oil & Gas Services & Equipment, Oil & Gas Producers, Construction Materials, Metals & Mining, Leisure Facilities & Services. *Unexposed* groups consist of Publishing & Broadcasting, Cable & Satellite, Internet Media & Services, Technology Services, Telecommunications, Entertainment Content, Industrial Support Services, Commercial Support Services, Advertising & Marketing, Consumer Services.[19]

5.1 Work Flexibility and Credit Lines Drawdowns

5.1.1 Industry Groups

We divide the level-1 sectors into three groups: *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. Thus, the proportions of *Exposed*, *Unexposed*, and *Mild* are 64.6%, 18.2%, and 17.2%, respectively. It suggests that more than half of the firms are exposed to the pandemic. Less than one-fifth of the firms could *survive* the pandemic and the corresponding social distancing policy.

Based on these three industry groups, we estimate the effect of social distancing on firms' credit line drawdowns, investment and cash holdings. We construct an industry fixed effect panel regression model, removing the time effect. We use the following specification:

$$Y_i \quad = \quad \alpha + \beta_1 (\textit{Industry Groups}_i \times \textit{2020:Q2}) + \gamma X_i + \epsilon_i \tag{10}$$

The dependent variable, Y_i, consists of: 1) Credit line usage, equal to the drawn amount relative to the total committed amount of credit lines; 2) Investment, equal to capital expenditure scaled by non-cash assets; and 3) Cash holdings, equal to cash scaled by non-cash assets. The *Industry Groups*$_i$ is, *Exposed*, *Unexposed*, and *Mild*, respectively. *2020:Q2* is a dummy equal to 1 indicating the time of the shock. X_i is a set of control variables like the ones in the previous sections. The interaction coefficient shows how the specific industry group performs during the shock period.

Table (19) shows the results. During the pandemic shock, only firms less exposed to the pandemic shock reduced credit lines (Panel A). The remaining firms used more of their credit lines than they usually did. All the firms reduced investments. In Panel B, we can see that the coefficients of the interactions are negative, and only the one for the group *Mild*×*2020:Q2* is significant. If we

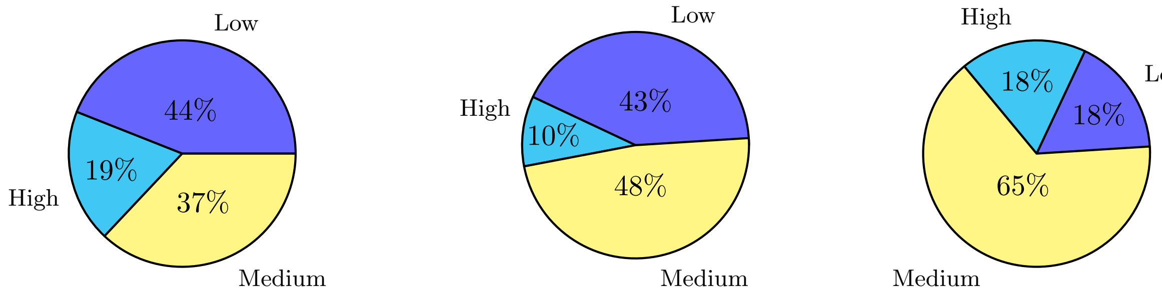
[19]Note that table (18) does not contain all the sectors or industries within the BICS. It merely displays the sectors or industry groups of our sampling firms.

consider cash holdings, both *Unexposed* and *Mild* increase the size of cash. The coefficient of the interaction *Exposed*$\times$*2020:Q2* is negative but insignificant.

In a nutshell, there is evidence that EU firms used their credit lines for precautionary reasons and not for investment. Panel A in Table (19) shows that over 80% of firms affected by the pandemic, to some extent, drew down their credit lines in anticipation of a liquidity shock and/or a worsening of their credit risk profile. Figure (11) shows that particularly firms within the group mild are firms with the worst EBITDA position among the three groups. These results are in line with what was already discussed earlier. At the start of the pandemic shock, firms affected by the lockdown (less work flexibility) saw a significant drop in their expected revenue. They responded by drawing down their credit lines and accumulating cash. These and previous results suggest a novel interplay between social distancing policies (work flexibility and, in part, country flexibility) and liquidity management as a new mechanism of firms' financial constraints.

	(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-non-cash 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-non-cash 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 19. **Regression Result: Industrial Exposure to COVID-19 (Euro Area)**. The dependent variables are credit line usage in Panel A, capital expenditure scaled by non-cash assets in Panel B, and cash holdings scaled by non-cash 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 are defined in the previous sections. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



(a). Exposed (b). Mild (c). Unexposed

Figure 11. The diagram shows the EBITDA by different exposure levels in 2020:Q2. The left diagram reports the proportions of *Low-*, *Medium-* and *High-EBITDA* within the *Exposed* group. The middle diagram reports the proportion within the *Mild* group. The right diagram reports the proportion within the *Unexposed* group.

5.2 Social Distancing Policies, Work Flexibility and Corporate Draw-down Decisions

There is a clear association between social distancing policies (work flexibility), firms' expected revenue, and panic borrowing. In this section, we extend the previous econometric setting and test the hypothesis that the inelastic nature of labour (less work flexibility) following the lockdown led to a sharp fall in revenue, especially in those industries more exposed to the pandemic shock. We introduce an indicator function:

$$I(Exposure) \quad = \quad \begin{cases} 1 & \text{if } Exposure \geq 0.75 \\ 0 & \text{if } Exposure \leq 0.3 \end{cases}. \tag{11}$$

This indicator captures two types of firms based on their risk exposure to the COVID-19 shock. To simplify, we only consider two groups: *Exposed* and *Unexposed* firms. As discussed earlier, we have also implemented a two-stage least-squares (2SLS) to account for possible endogeneity. The specification is as follows:

$$EBITDA_{i,t} \quad = \quad \delta_0 + \delta_1.I(Exposure) + \eta_{i,t} \tag{12}$$

$$\begin{aligned} Drawdown_{i,t} \quad = \quad & \beta_0 + \beta_1 \widehat{EBITDA}_{i,t} + \beta_2 \widehat{EBITDA}_{i,t} \times \mathit{2020{:}Q2} \\ & + \gamma X_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{13}$$

The first-stage regression in equation (12) relates EBITDA with the inelastic nature of labour in those firms more exposed to social distancing policies (less work flexibility). The second-stage regression in equation (13) shows how EBITDA affects drawdown decisions. $\widehat{EBITDA}_{i,t}$ denotes the fitted value of *EBITDA* from the first-stage regression.

Table (20) shows the results. Columns (1) across (3) show the OLS regression within three subsamples: (1) both *Exposed* and *Unexposed* firms, (2) *Exposed* firms, and (3) *Unexposed* ones. Exposed firms carry the most sizeable beta coefficient with the expected sign: a negative shock on EBITDA is associated with increased credit line draw-downs. As robustness, we also designed a regression with three-way interaction. Column (4) shows the results. The coefficient of the three-way interaction is significant, consistent with results in columns (1) to (3).

Finally, column (5) in Table (20) shows the results from our 2SLS. The coefficient of the interaction ($\widehat{EBITDA}_{i,t} \times 2020{:}Q2$) is significant at 10% level, implying that the inelastic nature of labour (less work flexibility) is important to understand firms' decisions to draw down credit lines. In a nutshell, work flexibility does help to understand the panic borrowing across European firms during the COVID-19 shock which led to credit lines drawdowns and cash accummulation.

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

Table 20. **Drawdowns on EBITDA during the COVID-19 crisis (OLS & 2SLS).** This table shows the estimations of Equation (13) 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. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Previous Crises

Is the work flexibility unique to the COVID-19 crisis? We will consider this important issue in the following sections. We start with the 2008 financial crisis and follow with the 2012 European crisis.

5.3.1 Work Flexibility During the 2008 Financial Crisis

Table (21) points towards weak empirical evidence that the financial crisis impacted firms' expected revenue in Europe, driving credit line drawdowns. Thus, work flexibility was not an issue during the 2008 financial crisis. The next section extends this to consider the European crisis.

Dependent Variable:	Drawdown Size				
	(1) OLS Two Firms	(2) OLS Exposed Firms	(3) OLS Unexposed Firms	(4) OLS 3-Way Interaction	(5) 2SLS Two Firms
$\text{EBITDA}_{i,t}$	-0.281***	-0.217*	-0.438	-0.159	0.119
	(0.107)	(0.122)	(0.274)	(0.215)	(0.346)
$\text{EBITDA}_{i,t}\times$2008:Q3	0.171	0.171	0.237	-0.599	-0.508
	(0.464)	(0.483)	(1.617)	(0.826)	(0.407)
$\text{I}(\text{Exposure}_i)$				0.039**	
				(0.016)	
$\text{EBITDA}_{i,t}\times\text{I}(\text{Exposure}_i)$				-0.056	
				(0.247)	
$\text{I}(\text{Exposure}_i)\times$2008:Q3				-0.013	
				(0.022)	
$\text{I}(\text{Exposure}_i)\times\text{EBITDA}_{i,t}\times$2008:Q3				0.790	
				(0.964)	
$\text{Leverage}_{i,t}$	0.100***	0.171***	0.065	0.117***	0.117***
	(0.025)	(0.032)	(0.067)	(0.027)	(0.023)
$\log(\text{Assets}_{i,t})$	0.001	-0.000	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Undrawn $\text{CL}_{i,t}$	0.110***	0.080**	0.159**	0.152***	0.171***
	(0.032)	(0.038)	(0.075)	(0.032)	(0.031)
$\log(\text{P/B}_{i,t})$	-0.005	0.002	-0.009	-0.008	-0.008
	(0.005)	(0.006)	(0.012)	(0.005)	(0.006)
Industry FE	yes	yes	yes	yes	yes
Times FE	yes	yes	yes	yes	yes
Observations	634	520	114	634	692
Adjusted R^2	0.123	0.110	0.158	0.111	0.095

Table 21. **Drawdowns on EBITDA during the 2008 financial crisis (OLS & 2SLS).** This table shows the estimations of Equation (13) 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 third quarter of 2008 (the Collaps of Lehman Brothers), and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2 Work Flexibility and the 2012 European Crisis

Table (22) shows the empirical results. Work flexibility was not associated with corporate decisions to draw down credit lines during the 2012 European crisis. In sum, the "panic borrowing" observed during the COVID-19 shock amongst European firms is unique to this crisis. These and previous results are new and interesting as they point towards a story where the nature of aggregate shocks matters to understanding firms' liquidity risk management. We are unaware of empirical papers investigating and discussing this important and new issue.

Dependent Variable:	Drawdown Size				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	2SLS
	Two	Exposed	Unexposed	3-Way	Two
	Firms	Firms	Firms	Interaction	Firms
$\text{EBITDA}_{i,t}$	-0.081	-0.042	-0.123	-0.244**	-0.222
	(0.055)	(0.058)	(0.143)	(0.103)	(0.290)
$\text{EBITDA}_{i,t}\times$2012:Q3	-0.128	-0.183	-0.342	-0.686	-0.411
	(0.131)	(0.123)	(1.902)	(1.036)	(0.414)
$\text{I}(\text{Exposure}_i)$				-0.001	
				(0.011)	
$\text{EBITDA}_{i,t}\times\text{I}(\text{Exposure}_i)$				0.222*	
				(0.120)	
$\text{I}(\text{Exposure}_i)\times$2012:Q3				-0.005	
				(0.011)	
$\text{I}(\text{Exposure}_i)\times\text{EBITDA}_{i,t}\times$2012:Q3				0.500	
				(1.045)	
$\text{Leverage}_{i,t}$	0.084***	0.053***	0.303***	0.087***	0.056***
	(0.018)	(0.018)	(0.060)	(0.018)	(0.018)
$\log(\text{Assets}_{i,t})$	-0.003***	-0.001	-0.019***	-0.003**	0.002
	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)
Undrawn $\text{CL}_{i,t}$	0.455***	0.370***	0.726***	0.465***	-0.001
	(0.033)	(0.035)	(0.088)	(0.032)	(0.002)
$\log(\text{P/B}_{i,t})$	0.002	0.000	-0.000	0.002	0.011***
	(0.003)	(0.003)	(0.010)	(0.003)	(0.003)
Industry FE	yes	yes	yes	yes	yes
Times FE	yes	yes	yes	yes	yes
Observations	1054	889	165	1054	1149
Adjusted R^2	0.199	0.156	0.365	0.194	0.015

Table 22. **Drawdowns on EBITDA during the 2012 European crisis (OLS & 2SLS).** This table shows the estimations of Equation (13) 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 third quarter of 2012 (the launch of monetary policies), and an indicator equal to one for highly exposed firms, and zero for unexposed firms. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusion

Why did European firms draw down credit lines and accumulate cash during the COVID-19 shock? We studied this vital issue in this paper. We showed that firms went into a sort of "panic borrowing" driven by an unexpected shortfall in revenue following the implementation of social distancing rules (and virus spread) across Europe. We also showed that firms with less work flexibility (or in countries with higher COVID cases) responded by dashing for cash. We showed that, in general, these firms had good solvency and liquidity positions. While these results are consistent with some theoretical models, see Acharya et al. (2012), they also open up more challenges for the same models as these consider credit lines exogenous, that is, means to support investment decisions. At the same time, the panic borrowing we report suggests that firms used credit lines for liquidity accumulation. We empirically implement a battery of econometric methodologies and quasi-natural experiments to investigate this issue. Finally, we showed a novel and exciting interplay mechanism between firms' work flexibility (somehow country flexibility), idiosyncratic risk and credit lines drawdowns leading to cash accumulation. Our results raise new questions for banks and governments. The pandemic shock introduced a new and significant source of firms' idiosyncratic risk, social distancing and work flexibility, and banks cannot ignore it when managing their loans portfolio. Also, our results make clear that a run on banks' credit lines can occur, and it depends on the nature of the aggregate risk (financial crisis vs COVID-19 shocks) and, probably, how this correlates with firms' idiosyncratic risk. These are important and new topics for theoretical and empirical research. Finally, our results also have implications for European governments when designing future lockdown policies. They suggest that clear and effective communication and considering work flexibility are essential to smooth the impact of aggregate shock and negative externalities from rum on credit lines and the fall of output.

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Appendices

A Capex on Drawdowns

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Regression results (using lagged variables)						
Drawdown Size$_{t-1}$	-0.016***	-0.017***	-0.045***	-0.046***	-0.091***	-0.085***
	(0.006)	(0.006)	(0.015)	(0.016)	(0.031)	(0.032)
Drawdown Size$_{t-1}$×2020:Q2		0.008		0.011		-0.026
		(0.021)		(0.033)		(0.038)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	366	366	293	293	389	389
R^2	0.233	0.233	0.225	0.226	0.221	0.222
B. Regression results (using contemporaneous variables)						
Drawdown Size$_t$	-0.015***	-0.016***	-0.048***	-0.048***	-0.141***	-0.136***
	(0.004)	(0.004)	(0.013)	(0.014)	(0.037)	(0.038)
Drawdown Size$_t$×2020:Q2		0.003		0.001		-0.020
		(0.010)		(0.029)		(0.042)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	707	707	364	364	486	486
R^2	0.192	0.192	0.241	0.241	0.240	0.240

Table A1. **Capital Expenditure on Drawdowns (Euro Area).** The table provides estimation results for lagged and contemporaneous specifications on the top and bottom panels, respectively. The dependent variable is capital expenditure scaled by total assets. The independent variables are drawdowns scaled by total assets and a time dummy indicating the second quarter of 2020. Columns (1) and (2) show the effect of the drawdowns on capital expenditures as a measure of investment decisions based on a benchmark estimation, whereas columns (3) across (6) show the corresponding impacts, based on two instruments, undrawn capacity and cash holdings in the previous period, respectively, to address the underlying endogeneity amongst drawdowns and investment decisions. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Cash Holdings

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Regression results (using lagged variables)						
Drawdown Size$_{t-1}$	0.116***	0.116***	0.264**	0.279**	2.991***	3.005***
	(0.039)	(0.041)	(0.107)	(0.113)	(0.163)	(0.170)
Drawdown Size$_{t-1}$×2020:Q2		-0.001		-0.109		-0.057
		(0.133)		(0.246)		(0.194)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	391	391	313	313	430	430
R^2	0.361	0.361	0.355	0.355	0.624	0.624
B. Regression results (using contemporaneous variables)						
Drawdown Size$_t$	-0.009	-0.004	0.196**	0.205**	4.384***	4.415***
	(0.025)	(0.027)	(0.081)	(0.089)	(0.143)	(0.147)
Drawdown Size$_t$×2020:Q2		-0.038		-0.050		-0.149
		(0.069)		(0.186)		(0.161)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	816	816	389	389	536	536
R^2	0.321	0.321	0.365	0.365	0.763	0.763

Table B1. **Cash Holdings on Drawdowns (Euro Area).** The table provides estimation results for lagged and contemporaneous specifications on the top and bottom panels, respectively. The dependent variable is cash and cash equivalents scaled by total assets. The independent variables are drawdowns scaled by total assets and a time dummy indicating the second quarter of 2020. Columns (1) and (2) show the effect of the drawdowns on cash holdings as a measure of precautionary motives based on a benchmark estimation, whereas columns (3) across (6) show the corresponding impacts, based on two instruments, undrawn capacity and cash holdings in the previous period, respectively, to address the underlying endogeneity amongst drawdowns and investment decisions. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C RID

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Different Time Dummies								
RID_{t-1}	0.037***	0.036***	0.043***	0.041***	0.123**	0.117**	0.151***	0.108*
	(0.012)	(0.012)	(0.012)	(0.015)	(0.049)	(0.050)	(0.052)	(0.063)
$\text{RID}_{t-1}\times$2020:Q1		0.027				0.150		
		(0.040)				(0.163)		
$\text{RID}_{t-1}\times$2020:Q2			-0.048*				-0.196*	
			(0.028)				(0.108)	
$\text{RID}_{t-1}\times$2020:Q3				-0.009				0.032
				(0.021)				(0.088)
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	388	388	388	388	381	381	381	381
Adjusted R^2	0.071	0.069	0.076	0.068	0.076	0.076	0.082	0.074
Panel B: Different Firm Types								
	(1) All Firms	(2) Low Risk	(3) Medium Risk	(4) High Risk	(5) All Firms	(6) Low Risk	(7) Medium Risk	(8) High Risk
RID_{t-1}	0.043***	0.016	-0.079	-0.083	0.151***	0.125	-0.196	0.185
	(0.012)	(0.017)	(0.074)	(0.132)	(0.052)	(0.111)	(0.231)	(0.502)
$\text{RID}_{t-1}\times$2020:Q2	-0.048*	-0.143***	0.015	0.071	-0.196*	-0.569*	0.270	0.286
	(0.028)	(0.045)	(0.152)	(0.217)	(0.108)	(0.294)	(0.473)	(0.822)
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	388	83	199	105	381	79	199	102
Adjusted R^2	0.076	0.109	0.026	0.187	0.082	0.017	0.102	0.236

Table C1. **Regression Result: RID Ratio on Drawdowns (Euro Area)**. The table provides the baseline models with various interactions and within different sub-samples. In columns (1) through (4), the dependent variables are the ratio of drawdowns size (*Drawdowns/TA*). In columns (5) through (8), the dependent variables are the usage of credit lines. Panel A reports the baseline models given the interactions between the RID ratio and time dummies (*2020:Q1, 2020:Q2*, and *2020:Q3*), respectively. Panel B reports the baseline models within the whole sample (*All Firms*) and three sub-samples (*Low-, Medium*, and *High-Risk*) based on firm types. 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) 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)
Distress$_t$×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 C2. **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/Non-Cash 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Alternative Regression Discontinuity Design

We also use a different econometric setting following Malenko & Shen (2016), to investigate if shocks on firms' earnings drive firms' decisions to draw down credit lines:

$$\begin{aligned} Drawdown_{i,t} &= \beta_0 + \beta_1 EBITDA_{i,t} + \beta_2 BelowCutoff_{i,t} + \beta_3 EBITDA_{i,t} \times \mathit{2020{:}Q2} \\ &\quad + \beta_4 BelowCutoff_{i,t} \times \mathit{2020{:}Q2} + \beta_5 BelowCutoff_{i,t} \times EBITDA_{i,t} \\ &\quad + \beta_6 BelowCutoff_{i,t} \times EBITDA_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{14}$$

where

$$BelowCutoff_t = \begin{cases} 1 & \text{if } Free\ Cash\ Flow_t \in [-\lambda, 0) \\ 0 & \text{if } Free\ Cash\ Flow_t \in [0, \lambda] \end{cases} \tag{15}$$

where λ denotes the bandwidth which is equal to half 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 firms (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 (12) shows the individual drawdown effects based on equation (7) 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 (13) shows the same effect based on the results in Table (D3).

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 D3. **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 cutoff point, and zero the firms are just above the cutoff 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 subsamples based on the performance just below the threshold. The rest columns use subsamples 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. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

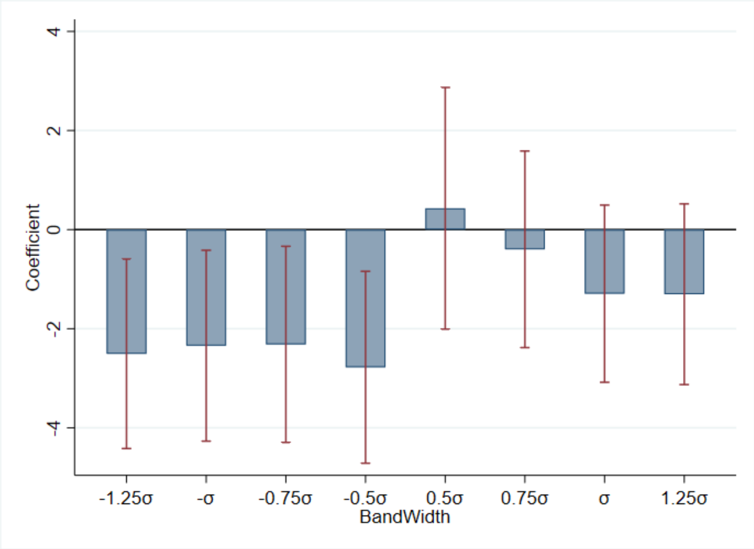

Figure 12. The diagram shows the estimated percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. The horizontal axis shows several bandwidth selections. Each value computed on the vertical axis is evaluated based on a separate estimation with an associated 95% confidence interval. The bandwidth selections considers even intervals around zero-earning outcomes and shows a sharp shift in the firms' behaviours to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.

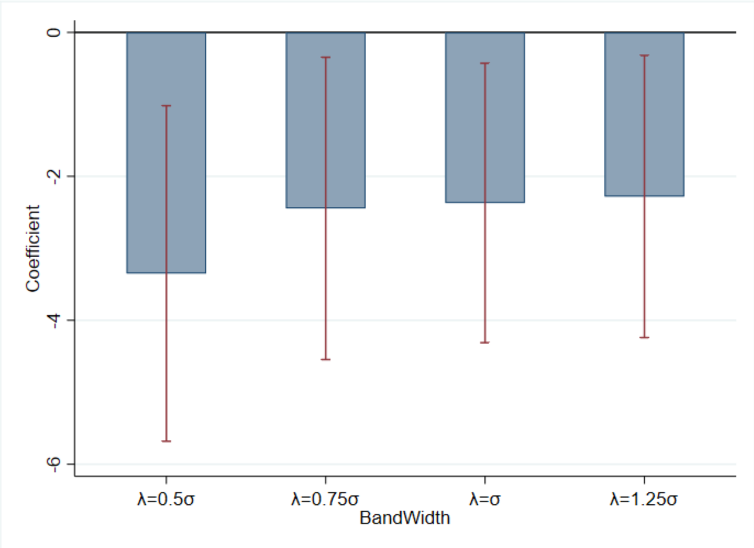

Figure 13. The diagram shows the estimated cross-sectional differential percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in draw down 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 summarising 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 considers even intervals around zero-earnings and shows a sharp shift in the firms' behaviours to draw down credit lines when facing marginally negative earnings while exhibiting no particular decision when facing marginally positive earnings.