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

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Abstract

We show that European firms, at the peak of the COVID-19 shock in 2020:Q2, went into a "panic borrowing" status and drew down €87bn in a very short period. We show that firms that drew down credit lines had less stringent solvency and liquidity constraints. Our study exploits the implications of the social distancing policies to corporate operations across Europe. The novel aspect of our study is that we focus on shocks unrelated to firms' fundamentals and investigate how firms manage their cash flow risk. It is an important novel aspect of this study as a large part of the literature has studied cash flow risk management following endogenous shocks due to bad management decisions. In doing so, we use COVID-19 infection data and proxies for social distancing policies in Europe as a natural laboratory. Finally, we show that European firms during the pandemic crisis increased drawdowns, 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. This result is driven by the lockdown policies introduced in Europe.

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. We estimate that European firms (the euro area) drew down over €87bn[1] 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) discussed similar results for US firms. Why did European firms draw down their credit lines at the start of the pandemic shock (2020:Q2)? This paper studies firms' liquidity management when hit by an unpredictable shock that is completely exogenous to firms' fundamentals and is likely to affect only firms' short-term financing needs. Brown et al. (2021) study a similar shock due to heavy snow. In this paper, we generalise and extend that idea to study firms' liquidity management and COVID-19 shock.

We show novel results. First, good European firms at the peak of the COVID-19 shock went into a "panic borrowing status" and drew down credit lines. We show a significant heterogeneity amongst borrowers. Firms highly exposed to the COVID-19 shock drew down credit lines and accumulated cash. These results have important policy implications and help us understand corporate liquidity management when shocks are not related to firms' fundamentals. In a nutshell, we study firms' credit insurance needs when hit by a shock unrelated to firms' fundamentals. At the same time, most of the literature has focused on liquidity risk management when firms are hit by shocks which are endogenous to the firm (Campello et al. 2011, Acharya et al. 2012). Studying COVID-19 shock and how this impacts cash flow and demand for credit insurance is interesting as the COVID-19 shock is not endogenous to the firm; it is not the consequence of bad management decisions. On the other hand, differently than the heavy snow shock (Brown et al. 2021), this is likely to raise aggregate risk and raise the demand for credit insurance by firms more exposed to it. Acharya et al. (2013) show that shocks increasing aggregate risk can limit the amount of credit insurance available to firms. We show that this was not the case during the COVID-19 shock (2020Q1 and 2020Q2), as banks worked together with firms to provide credit insurance for liquidity risk management. Banks helped firms hit by this shock to manage their (short-term) liquidity. Finally, another contribution of this study is that we use a battery of novel econometric settings to empirically identify the channel through which the shock affects firms' short-term credit needs.

The COVID-19 shock led to a policy response across Europe which was not uniform (we call it country flexibility). Social distancing policies across European countries were very different in different countries. Did different social distancing policies contribute to the "panic borrowing"? We are not aware of other studies investigating such important issues. We employ infection rates in Europe and a proxy for social distancing policy in a given country (Oxford Stringency Index). We show that country flexibility is important. Firms in countries where COVID-19 infection rates were higher than the rest 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 necessary to understand job hiring 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 also

[1]We also use Capital IQ as an alternative database. We find that our Bloomberg database in this paper can accout for 80% of credit line drawdowns in the same Euro area within the same period, which is satisfying.

important to understanding firms' behaviour, such as 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.

In a nutshell, the panic borrowing in Europe seems unique to the COVID-19 crisis, driven by the social distancing policies introduced in Europe. These are new and significant results as they suggest that the nature of the shock (COVID-19 shock vs financial crisis shock or heavy snow) does matter to understand why European firms draw down credit lines and accumulate cash. Finally, 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 or work flexibility) associated with firms' idiosyncratic risk.

As we mentioned above, the majority of papers studying credit lines for liquidity risk management (Holmström & Tirole 1998, Sufi 2009, Acharya et al. 2014) focused on firms having long-term operational problems and/or liquidity constraints. We extend this literature and consider firms which do not experience liquidity constraints and do not face long-term operational problems. Thus, we study how financially unconstrained firms manage liquidity shocks which are likely to impact only short-term financing needs. We show evidence that financially unconstrained firms drew down credit lines in 2020Q1 and, at the peak of the shock in 2020Q2. This panic borrowing lasted two quarters (2020Q1 to 2020Q2) and did not extend to 2020Q3. These results are also in line with those for US firms as discussed in Acharya et al. (2020), suggesting a higher degree of international corporate market integration.

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. In this respect, our study on European firms complements others focusing on the US market (for example, Acharya et al. (2020)) by studying international financial and corporate markets integrations as pointed out in Berg et al. (2017).

Firms' liquidity risk management has been investigated in the literature. However, most of the focus has been on whether insurance liquidity is used for investment or rather precautionary reasons (Li et al. (2020), and Greenwald et al. (2021) Bosshardt & Kakhbod (2020)). We speak to this literature as we show that our firms are financially in a good position (Papanikolaou & Schmidt 2022), but the shock had a heterogeneous effect on how they managed liquidity risk. 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. Following Campello et al. (2011, 2020), we extend this setting, employ infection rates and a proxy for social distancing policies in Europe, and show significant heterogeneity in the way European firms were hit by the COVID-19 shock and their decision to draw credit lines. We show that work flexibility triggered this unexpected shock and the following "panic borrowing".

Figure (1) shows the total amount (in billions of euros) of credit line drawdowns 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 most prominent 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 shows 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.

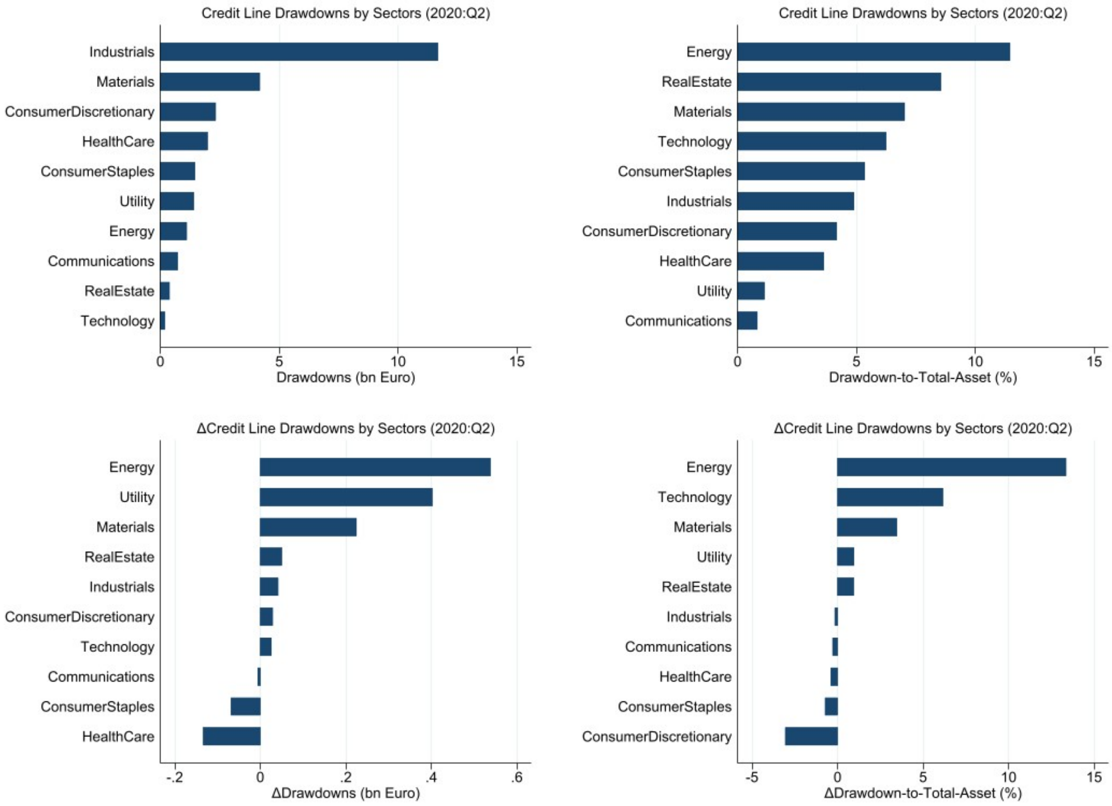


Figure 1. The top left diagram shows credit line drawdowns in different sectors during the second quarter of 2020, followed by similar quarterly changes between 2020:Q1-Q2. The diagram on the bottom-left shows the changes in credit line drawdowns in 2020:Q2, compared with the previous quarter. The horizontal 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 holdings) and external (credit lines) fundings using data when credit was abundant. He shows that firms using credit lines are generally profitable, while those facing a fall in cash flow find it difficult to access credit needs through credit lines exactly when they need it the most. Acharya et al. (2014) explain why banks revoke credit lines to unprofitable firms. Campello et al. (2011), using data for the 2008 financial crisis and US firms report a substitution effect between cash holding and credit lines when firms face a severe credit shortage. We extend and complement these studies by using the COVID-19 shock as a natural laboratory to study how good firms manage liquidity shocks uncorrelated to fundamentals. Finally, some of our results in the second part of this paper also speak to the growing and recent literature on the effect of natural events on firms' liquidity risk management (Koetter et al. 2020, Brown et al. 2021).

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).[2]

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.[3] The drawdown size, drawdown-to-total assets ratio, is about 5 per cent and the undrawn size, undrawn amount of credit line scaled by total assets, is about 12 per cent.

We adjust some financial variables by total assets. Accordingly, *Cash Holdings* represents the cash and cash equivalent scaled by total assets. *Cash Flow*, *CAPEX*, and *Tangible Assets* are cash flow, capital expenditure and tangible assets scaled by total assets separately. *Log(assets)* is the natural logarithm of total 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.** This table shows the descriptive statistics of 324 non-financial firms in the Euro Area during 2018:Q4 - 2020:Q3. Appendix (A) provides the definition of all variables.

Revolving credit lines are facilities commonly used by banks to supply cash to firms. Figure (2) shows the weighted credit line drawdowns and credit lines drawdown size for all Euro-area firms in

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

[3]Credit line usage is measured by the ratio of drawn-down to the total amount. The undrawn rate is equal to one minus credit line usage.

the sample. In the left-hand-side panel, we scale drawdowns by the number of firms each quarter.[4] European firms drew down credit lines at the start of the pandemic and in the following months.

We also note a significant increase in cash holdings during the same period. The increase in cash holdings could be associated with 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, probably to mitigate the impact of possible liquidity shocks. In a nutshell, EU firms may have taken out of their credit lines in anticipation of a possible liquidity shock. However, credit line drawdowns can also be associated with investments. In Figure (3B), we use capital expenditure as a proxy 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. However, they do not study firms' investments during the COVID-19 period. Bosshardt & Kakhbod (2020) show similar evidence. In Online Appendix, we support these findings using a panel regression and capital expenditure as a dependent variable. We do not find evidence that firms used credit lines to support investments in 2020:Q2.

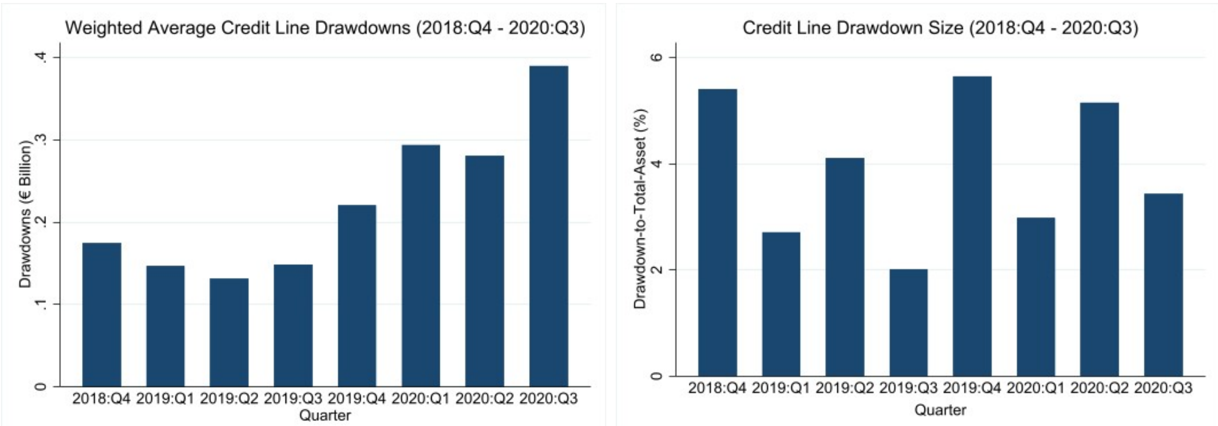


Figure 2. The left diagram reports the average credit line drawdowns in the firm level during 2018:Q4 - 2020:Q3. The right diagram reports the drawdowns scaled by total assets during the same period.

[4]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.

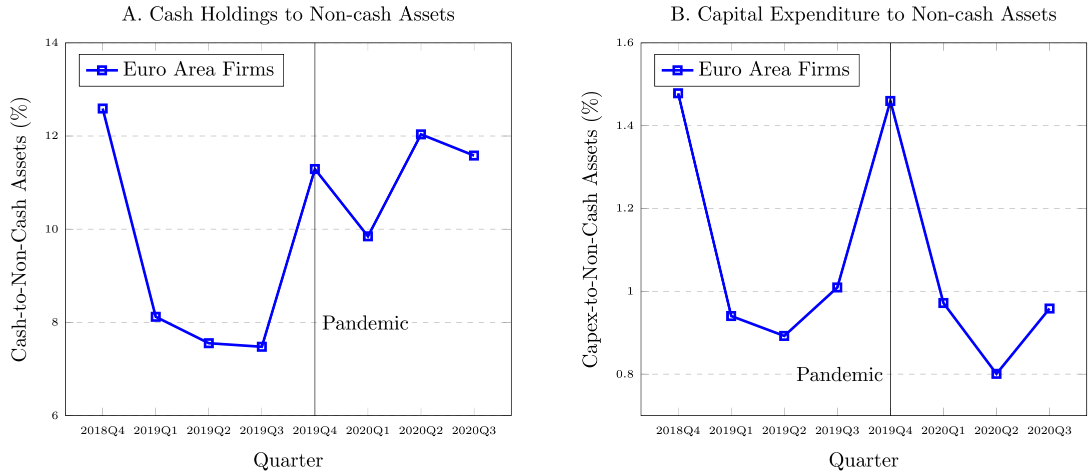


Figure 3. The left diagram reports the average cash-to-non-cash-assets ratio in the firm level during 2018:Q4 - 2020:Q3. The right diagram reports the average capital-expenditure-to-non-cash-assets ratio in the firm level during the same period. The horizontal axes in two diagrams are the quarters, while the vertical axes are the percentage number.

3 Financial Constraints

In this section, we show that firms drawing down credit lines at the peak of the COVID-19 shock mainly had good solvency and liquidity position. Sufi (2009) shows that less financially constrained firms generally rely on credit lines while financially constrained firms use cash to manage liquidity shocks. The main issue with Sufi's study is that the period studied was when credit was abundant, which may have driven the empirical results. Campello et al. (2011) study the financial crisis period. They show that firms substitute between internal (cash holding) and external liquidity (credit lines) in the presence of liquidity shocks. However, the main focus of that study is on firms' real side (investment) decisions and credit lines. Acharya & Steffen (2020*b*) study the recent COVID-19 period and how firms raise cash to offset changes in credit risk following the COVID-19 shock. They show that credit risk is important to understand how US firms raised cash during the pandemic and why they dashed for cash. This section builds on this literature with the main focus being to study whether borrowers, at the peak of the COVID-19 shock, were financially constrained (Almeida et al. 2004, Bates et al. 2009). In the Appendix B, we show detailed results for firms under solvency (Acharya et al. 2012) and liquidity constraints. In Table (2) (solvency risk) and Table (3) (liquidity risk) below, we summarise our results and divide firms (in 2020:Q2) into three groups according to the RID: Low Risk (25%), Medium Risk (50%) and High Risk (25%).[5]

For the full sample, the coefficients in the three groups are statistically insignificant, while they are significant in 2020:Q2 for the Low-Risk group. That is, lower-risk firms (in terms of solvency) drew down their credit lines in 2020:Q2. Figure (A9) shows the change in credit lines between two quarters (for each of the three groups) between 2020:Q1 and 2020:Q2. Figure (A9) 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. There is a negative association between credit line drawdowns and solvency risk in 2020:Q2. In a nutshell, firms with a good solvency position drew down their credit lines during the COVID-19 shock and topped up their cash holding position.[6]

[5]We also considered alternative combinations, and results stay unchanged. Results are available upon request.
[6]We have also included Cash Holdings in Table (A25) and the coefficients are significant but positive. Therefore,

Why did these firms draw down credit lines at the peak of the COVID-19 shock? In the next sections, we shall use the COVID-19 shock as a natural laboratory to study firms' liquidity risk management following the COVID-19 shock.

	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
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}×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 2. **RID Ratio and Drawdowns (Euro Area)** This table shows the results of the baseline models in equation (12) 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 credit lines usage. 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 for the whole sample (*All Firms*) and three sub-samples (*Low-, Medium-*, and *High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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)
$Distress_t$×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 3. **Credit Lines Drawdowns and Distress by Firm Types**. This table shows the results of the baseline models in equation (15) within different sub-samples based on firm types. The dependent variable in columns (1) to (4) is credit line drawdowns scaled by total assets. The dependent variable in columns (5) to (8) is the usage of credit lines. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between the distress and time dummies (*2020:Q2*). Apart from the whole sample (columns (1) and (5)), the regression is also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we exclude that a substitution effect between internal and external funding occurred in 2020:Q2.

3.1 Shortfall in Revenue and Credit Lines Drawdowns

Why did firms draw down credit lines in 2020:Q2? This is an interesting question given that it is implausible that the COVID-19 shock has affected the long-term investment plans of these firms (as they are financially unconstrained) but only short-term ones. In this section, we investigate 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 predicted a significant shortfall in revenue (or cash flow) and drew down their credit lines to increase cash holdings. A shortfall in revenue following the COVID-19 shock can significantly affect a firm's short-term financing requirements. Therefore, the panic borrowing we observe in the data is likely to result from an unexpected shortfall in revenue. We are not aware of other studies which explicitly study this for the COVID-19 period. While Brown et al. (2021) study the effect of severe winter weather on firms' decisions to use credit lines to manage liquidity shocks, we consider a more persistent shock such as the one induced by the COVID-19 lockdown. We use cash flow as measured by the EBITDA, net income with interests, taxes, depreciation, and amortization, and include time and industry fixed effects:

$$\begin{aligned}\text{Drawdown}_{i,t} \quad = \quad & \beta_0 + \beta_1 \text{EBITDA}_{i,t} + \beta_2 \text{EBITDA}_{i,t} \times 2020\text{:Q2} + \\ & \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

where *Drawdown* is a ratio with respect firms' total assets and *2020:Q2* is a dummy indicating the pandemic period. The specification includes a set of controls $X_{i,t}$ containing cash holding, financial constraints, the undrawn amount of credit lines, tangible assets scaled by total assets, the natural logarithm of total assets, the price-to-book ratio, and the leverage ratio. Time and industry fixed effects are included. We consider firms with at least one observation before and after 2020:Q2.[7]

We show the results using contemporaneous and lagged specifications in Table (4) and Table (5), respectively, and 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 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. 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 impact on credit line drawdowns. Credit line usage results are summarized in columns (4) to (6). We note marginally significant cash holdings in very few cases. Overall, these results are similar using lags and contemporaneous specifications and support our assumption that, at the start of the pandemic shock, an unexpected fall in revenue led firms, with good liquidity (solvency) positions, to draw down credit lines. These results support our conjecture that Europe's "panic borrowing" in 2020:Q2 was significant. In the next section, we show that the "panic borrowing", following the unexpected (largely unknown) shock, affected a large part of the European economy.

In Table (6), we divided firms into Low-, Medium- and High-EBITDA to further shed light on these results. In 2020:Q2, the dummy coefficient is only significant for firms with lower EBITDA,

[7]Results not included in this paper show that, the results we report in this section are robust after accounting for survival bias particularly when a certain fraction of firms face bankruptcies. These results are available upon request.

and this coefficient carries a negative sign. Therefore, in 2020:Q2, firms whose cash flow was expected to be hit by the COVID-19 shock drew down their credit lines and increased cash holdings. While these results support the "panic borrowing" status, they also point towards the possibility of an endogenous role of credit lines drawdowns in firms' decisions. We shall consider this in the next section. Figure (4) shows, for the three groups, the change in cash holdings between 2020:Q1 and 2020:Q2. The low EBITDA group shows the most considerable change in cash holdings. The right diagram shows that low-risk firms (low solvency risk firms) experienced the most significant drop in EBITDA in 2020:Q2.

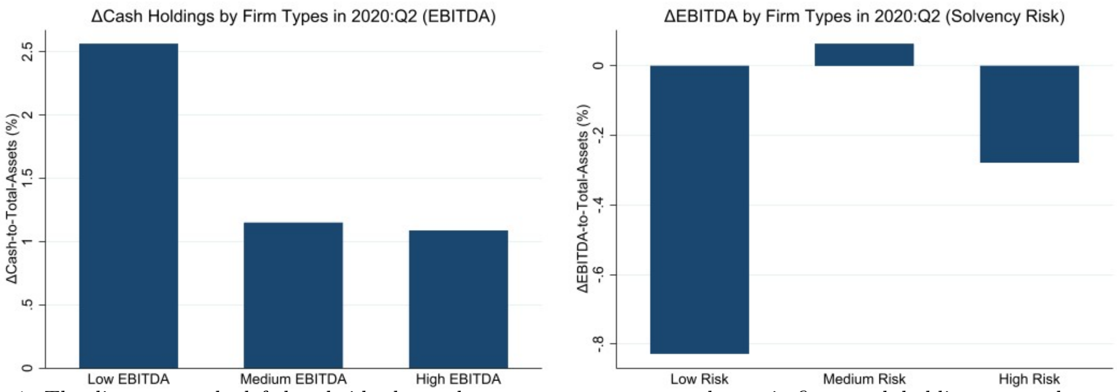


Figure 4. The diagram on the left-hand-side shows the aggregate percentage change in firms cash holdings to total assets ratio by the underlying earning status, low, medium and high, respectively, which shows firms within the lowest status increased their cash holdings relatively twice the other groups between the 2020:Q1-Q2. The diagram on the right-hand-side shows the aggregate percentage changes in the earnings between 2020:Q1-Q2 according to the firms underlying risk profiles.

3.2 Credit Lines Drawdowns and Revenues: a Discontinuity Analysis

In the next sections, we complement the previous results by using two different econometric settings to empirically identify the effect of the fall in cash flow on firms' credit line drawdowns. Furthermore, since the "panic borrowing" might point towards endogeneity in firms' decisions to draw down credit lines and accumulate cash, these econometric settings also help us to control for this. We are unaware of empirical (theoretical) studies that have addressed this issue explicitly.

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:

$$\text{Drawdown}_{i,t} \quad = \quad \beta_0 + \beta_1 D_{i,t}(\lambda) + \beta_2 D_{i,t}(\lambda) \times 2020\text{:Q2} + \gamma X_{i,t} + \epsilon_{i,t} \tag{2}$$

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.[8] The notations follow the definition in equation (1) and 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 study 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.

[8]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.

	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 4. **Credit Lines Drawdowns and 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) All Firms	(2) Low Distress	(3) High Distress	(4) All Firms	(5) Low Distress	(6) 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)
EBITDA$_{t-1}$×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)
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(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)
EBITDA$_{t-1}$×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)
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(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)
EBITDA$_{t-1}$×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)
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(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 5. **Credit Lines Drawdowns and 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 6. **Credit Lines Drawdowns and EBITDA by firm types.** This table shows the results of the baseline models in equation (15) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results are presented in Table (7), 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 important to understand why using 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 empirical evidence in support of the "panic borrowing" is quite robust and seems to be driven by a shortfall in firms' revenue.[9]

[9] Appendix D reports an alternative design of regression discontinuity where we show that the empirical evidence in Table (7) is robust.

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\times$2020:Q2	-3.173***	0.873	-2.778***	0.430	-2.316**	-0.398	-2.343**	-1.293	-2.507**	-1.305
	(1.005)	(3.851)	(0.975)	(1.236)	(1.000)	(1.008)	(0.974)	(0.909)	(0.967)	(0.928)
log(Assets$_t$)	0.000	-0.012**	-0.005	-0.009**	-0.005	-0.012***	-0.005	-0.008***	-0.005	-0.009***
	(0.007)	(0.006)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)
Leverage$_t$	0.085	0.090	0.125*	0.078*	0.135**	0.077**	0.145**	0.068**	0.111*	0.064**
	(0.067)	(0.060)	(0.065)	(0.040)	(0.063)	(0.032)	(0.061)	(0.028)	(0.059)	(0.028)
Undrawn CL$_t$	0.337***	0.425***	0.312***	0.352***	0.287***	0.263***	0.284***	0.283***	0.271***	0.243***
	(0.098)	(0.091)	(0.089)	(0.066)	(0.091)	(0.052)	(0.090)	(0.046)	(0.088)	(0.042)
log(Price$_t$)	0.003	0.007	0.005	0.009	0.000	0.004	0.001	0.001	0.002	0.003
	(0.012)	(0.009)	(0.010)	(0.006)	(0.009)	(0.005)	(0.009)	(0.004)	(0.008)	(0.004)
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	85	110	115	213	149	309	157	387	169	427
Adjusted R^2	0.237	0.267	0.253	0.208	0.150	0.153	0.148	0.148	0.121	0.133

Table 7. **Regression Discontinuity Design and Credit Lines Drawdowns**. This table shows credit line drawdowns on revenue within various groups based on cash flow. The dependent variable is *Drawdown Size*, is credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included. Columns (1), (3), (5), (7), and (9) use 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 During the 2008-2012 Crises

Is the "panic borrowing" unique to the pandemic crisis? Answering this question is important to understand if a type of shock matters to firms' preference for credit line drawdowns and cash accumulation. To address this question, we compare the impact of the COVID-19 shock with that of the 2008 - 2012 financial and European crises. The results in this section as well as in Section 6.3 below, can also be interpreted as an empirical identification attempt to show that the COVID-19 shock has been key to driving firms' demand for insurance credit at the peak of the COVID-19 shock. In contrast, the shock studied in Brown et al. (2021) is mainly idiosyncratic. This gives us a first insight into how different shocks drive firms' decisions for liquidity insurance. In fact, although the COVID-19 shock has impacted aggregate risk, it is unlikely that, as it happened with the financial crisis shock, it has had a significant impact on firms' long-term investment plans. Of course, these two shocks are also 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 and financial constraints. Our paper also speaks to this part of the literature but focuses mainly on credit line drawdowns and European firms.

4.1 European Firms and The Financial Crisis

4.1.1 The 2008 Financial Crisis and Credit Lines Drawdowns

In Table (8) to Table (10), we use solvency and liquidity constraints and study if European firms hit by the 2008 financial crisis drew down their credit lines. We show the results for the 2008:Q2 - 2008:Q4 period.[10]

In general, if we consider all the firms, there is a negative association between firms' solvency (Table (8)), liquidity (Table (9)) risk, and credit lines drawdowns. Furthermore, there is weak evidence that the financial crisis's shock is associated with European firms' decisions to draw down credit lines. For all the firms, there is evidence that they 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 what was documented for the US, acted as a detonator leading to a dash for cash.[11]

4.1.2 The 2012 European Crisis and Credit Lines Drawdowns

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. We show the results in Table (11) to Table (13).[12]

Firms' solvency risk is not always significant and is negatively associated with firms' decisions to draw down credit lines. The empirical evidence is also weak when liquidity constraints are

[10] As for the 2008 financial crisis, we collect quarterly data from 2007:Q1 to 2009:Q3, including 443 non-financial firms and 1,446 observations.

[11] We also used Cash Holdings in Table (8). Cash holding is generally significant and positive for RID but insignificant and negative for liquidity distress. It seems to suggest weak evidence of cash holdings accumulation for European firms during the financial crisis.) In Table (10), coefficients are all generally highly significant, but with RID, they carry a positive sign. These are negative in the case of Distress and EBITDA.

[12] As for the 2012 European crisis, we collect quarterly data from 2009:Q4 to 2013:Q4, including 1,046 non-financial firms and 5,983 observations.

introduced (Table (12)) and also for firms hit by a shortfall in revenue (Table (13)). Overall, there is weak evidence that the 2012 European crisis acted as a detonator for firms to dash for cash. These results show that the COVID-19 shock is unique. Following that shock, European firms drew down their credit lines for precautionary motives driven by a "panic borrowing".[13] 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).

	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)
$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)
$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)
$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 8. **Credit Lines Drawdowns and Solvency Risk in 2008 Financial Crisis**. This table shows the results of the baseline models in equation (12) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[13]We also include Cash Holdings in Table (11) to Table (13). The coefficients are generally highly significant, once again positive for RID and negative for Distress and EBITDA.

	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 9. **Credit Lines Drawdowns and Liquidity Distress in 2008 Financial Crisis**. This table shows the results of the baseline models in equation (15) 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 \times$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 \times$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 \times$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 10. **Credit Lines Drawdowns and Cash Flow During the 2008 Financial Crisis**. This table shows the results of the baseline models in equation (1) 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 11. **Credit Lines Drawdowns and Solvency Risk During the 2012 European Crisis**. This table shows the results of the baseline models in equation (12) 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 12. **Credit Lines Drawdowns and Liquidity Distress During the 2012 European Crisis**. This table shows the results of the baseline models in equation (15) 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 13. **Credit Lines Drawdowns and Cash Flow During the 2012 European Crisis**. This table shows the results of the baseline models in equation (1) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 COVID Impact

5.1 Lockdown Policies, Credit Lines Drawdowns and Cash Accumulation

We showed that during the COVID-19 shock, European firms went into a "panic borrowing" driven by an unexpectedly sharp fall in revenue. Thie panic borrowing is unique to the COVID-19 shock and has 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. To define country flexibility, we consider the country's infection data and specific social distancing policy (less or more stringent). We borrow this approach from Campello et al. (2020), who study job hiring in the US and work flexibility. The idea of doing this is twofold. Firstly, it will allow us to directly use information reported on COVID-19 cases to define the COVID-19 shock and to study if the "panic borrowing" is a consequence of high COVID-19 cases and 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, as explained, we follow Campello et al. (2020) and define high (low) COVID-19 impact within a specific country (we consider the COVID-19 cases in the largest European economies: Germany, France, Italy and Spain). 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.

5.1.1 Infection Rates, Mobility Policy and Credit Lines Drawdowns

We use Equation (3) below to study the relationship between infection rates (mobility policy) and firms' credit lines draw downs.

$$
\begin{aligned}
Drawdown_{i,t} &= \alpha + \beta_1 \textit{COVID Impact}_{i,t} + \beta_2(\textit{COVID Impact}_{i,t} \times \textit{2020:Q2}) \\
&\quad + \gamma X_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

where $Drawdown_{i,t}$ denotes: 1) credit line drawdowns divided by total assets, and 2) credit line usage. $\textit{COVID Impact}_{i,t}$ is once 1). $\textit{High COVID Exposure}_{i,t}$, 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 $\log(\textit{Stringency})$, 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 (3) are documented in Table (14).

Table (14) 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. Finally, the 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 14. **The impact of COVID-19 on Credit Line Drawdowns During the COVID-19 Shock**. This table presents the regression results of Equation (3). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.1.2 Social Distancing Policies Across European Countries

Given that European countries have used different mobility policy rules during COVID-19, 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 European social distancing policies that can help us understand why firms drew down their credit lines and piled up cash? Figure (5) 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:

$$\begin{aligned} Drawdown_{i,t} &= \alpha + \beta_1 log(Stringency)_{i,t} + \beta_2 (log(Stringency)_{i,t} \times Country_i) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

where $Drawdown_{i,t}$ has same definition as previous specifications. $\log(Stringency)_{i,t}$ indicates the logarithm of the Stringency Index which records the strictness of "lockdown style" policies. $Country_i$ is an indicator of different countries including Italy, Germany, France, and Spain. The controls have same definitions as previous specifications. Table (15) reports the regression results of Equation (4).

The relationship between the stringency index and credit lines draw down is positive and significant across all the 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. Although our results are not conclusive, and we acknowledge the need for further investigation in the future, they seem to suggest that the different lockdown measures across European countries have somehow had an impact on firms' decisions to draw down credit lines and accumulate cash. 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.[14] These results have important policy implications given that social distancing policies can generate negative externalities for firms and unexpectedly fly to liquidity.[15]

[14] We have also considered different quarters in our analysis. Results are available upon request.

[15] Credit line drawdowns also have serious implications for banks' liquidity management. As we discussed earlier, firms rely on credit lines as insurance, especially in bad states. Our results suggest that country flexibility is important, although more work is necessary to study country flexibility and credit line drawdowns.

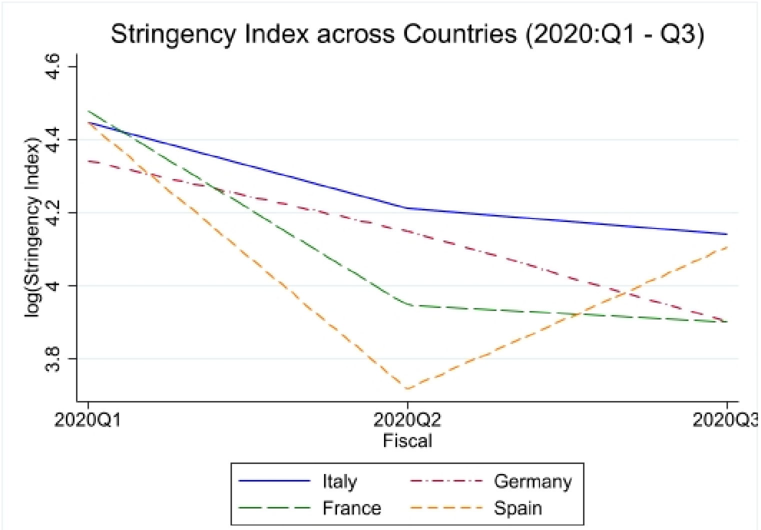


Figure 5. This diagram shows the strictness of lockdown policy across main European countries. The horizontal axis shows the three quarters when the COVID-19 pandemic burst. The vertical axis shows the logarithm of the Stringency Index which measures the strictness of 'lockdown style' policies.

	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 15. **The impact of COVID-19 on Credit Line Drawdowns (Countries).** This table shows the regression results of Eq. (4). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Empirical Identification

In this section, we complement the previous results by using an additional empirical framework to identify whether the COVID-19 shock (lockdowns) has driven corporate liquidity management decisions to draw credit lines through its effect on expected revenue. We use the same econometric setting as in Brown et al. (2021). The empirical strategy allows one to disentangle the causal effect of a change in cash flow on credit lines drawdowns. We use a 2SLS procedure:

$$EBITDA_{i,t} = \alpha + \beta_1 log(Cases)_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{5}$$

$$Drawdown_{i,t} = \alpha + \beta_1 \widehat{EBITDA}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{6}$$

where the first stage is given by equation (5) and the number of reported cases across countries. In the second stage, equation (6), we regress drawdowns on predicted values from the first stage and a set of controls as in the first stage. All variables are defined as in the previous sections. Given that the COVID-19 shock was completely unpredictable by firms, the assumption is that it has no (or very little) effect on long-term investment decisions but only affects short-term liquidity risk. Therefore, we can study firms' liquidity risk management when shocks are uncorrelated with firms' (long-term) investment decisions.

Figure (6) shows the results from the first stage regression and confidence interval in each quarter between 2020Q1 and 2020Q3. The estimated change in cash flow, given the number of COVID-19 cases, decreased between 2020Q1 and 2020Q2 but increased thereafter. Firms responded to this shock by drawing their credit lines during that quarter. Table (16) shows the results from the 2SLS. The empirical results are from two specifications. OLS in columns (1), (3) and (5), as well as 2SLS in columns (2), (4) and (6). We report the results for 2020Q1-2020Q3. They will help us understand if the panic borrowing is mainly concentrated in 2020Q2 or extends to 2020Q3. The estimated beta is highly significant in 2020Q2 and significant in 2020Q1 but becomes insignificant in 2020Q3. Also, the estimated size of the coefficient is much larger in 2020Q2, confirming that the panic borrowing is mainly concentrated in this quarter, and firms managed the liquidity shock by drawing their credit lines. In sum, the empirical evidence confirms what we reported in the previous sections. It suggests that the COVID-19 shock in 2020Q2 affected firms' decisions to draw their credit lines through its impact on expected revenue.

The empirical results in Table (16) Panel A suggest that in 2020Q1 and 2020Q2, European firms used credit lines to manage liquidity risk. It is interesting to study whether banks, given the increased aggregate risk following the shock, worked with firms to provide liquidity. To study this, in Panel B, we use the same econometric framework as in Panel A but with credit line size (scaled by total assets) as an instrument in the second stage regression. The negative coefficient on cash flow indicates that banks accommodated firms during the COVID-19 shock, providing them with the necessary insurance credit.[16] In the next section, we shall extend this study to understand if banks accommodate all the firms or if they consider the heterogeneous impact of COVID-19 (i.e. work flexibility) when providing credit insurance.

[16] An interesting question is how banks could do this during COVID-19 while they withdrew credit insurance during the 2008 financial crisis. We leave this on the agenda for future research.

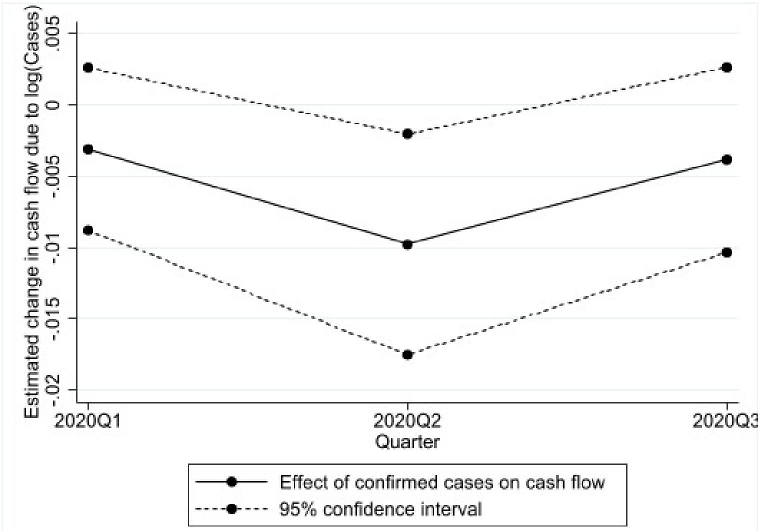


Figure 6. Cash flow and COVID confirmed cases. This figure shows the relationship between *log(Cases)* and firms' cash flow. The figure is estimated from three regressions of Equation (5), one for each quarter during 2020:Q1-Q3. The solid line represents the estimates of *log(Cases)* on cash flow (i.e. *EBITDA*). The short-dash line represents the 95% confidence intervals on the estimation.

	Panel A					
	Drawdown Size					
	2020:Q1		2020:Q2		2020:Q3	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
EBITDA_t	-0.676	-9.929**	-1.752***	-18.649***	-0.121	-7.304
	(0.738)	(4.087)	(0.610)	(6.655)	(0.712)	(6.281)
Controls	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Observations	56	56	81	88	62	63
R^2	0.158	0.249	0.300	0.264	0.117	0.143
	Panel B					
	Total Credit Line Size					
	2020:Q1		2020:Q2		2020:Q3	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
EBITDA_t	-0.676	-9.929**	-1.752***	-18.797***	-0.172	-8.083
	(0.738)	(4.087)	(0.610)	(6.671)	(0.755)	(6.655)
Controls	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Observations	56	56	81	88	62	63
R^2	0.672	0.708	0.706	0.664	0.607	0.623

Table 16. **Two-Stage Least Square (2SLS) Identification Strategy.** This table reports both the OLS and 2SLS regression results of Equation (6) in different quarters. In panel A, the dependent variables is credit line drawdowns scaled by total assets. The independent variables are the EBITDA scaled by total assets. Controls contain unused credit lines, the logarithm of price-to-book ratio, tangible assets, and the leverage ratio. Columns (1), (3), and (5) are based on OLS regression within the first three quarters in 2020. Columns (2), (4), and (6) use log($Cases$) as instrumental variable. Panel B uses total committed credit lines as dependent variables. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Industrial Exposure to COVID-19 and Credit Lines Drawdowns

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 this was driven by an unexpected shortfall in firms' revenue, which differed across countries. We name work flexibility as the capacity to perform a job from home. The results in the next section complement and extend the ones reported earlier. Bosshardt & Kakhbod (2020) showed that the economic shutdown motivated firms to draw down their credit lines for precautionary reasons 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). The idiosyncratic effect of COVID-19 across different industries 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.

To define work flexibility, in this section, 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:

$$Exposure \;\; = \;\; 1 - Job\ Done\ at\ Home$$

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,[17] 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 (17) shows the industrial exposure to COVID-19 within two industrial levels. In Figure (7), 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 (17) 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 In-

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

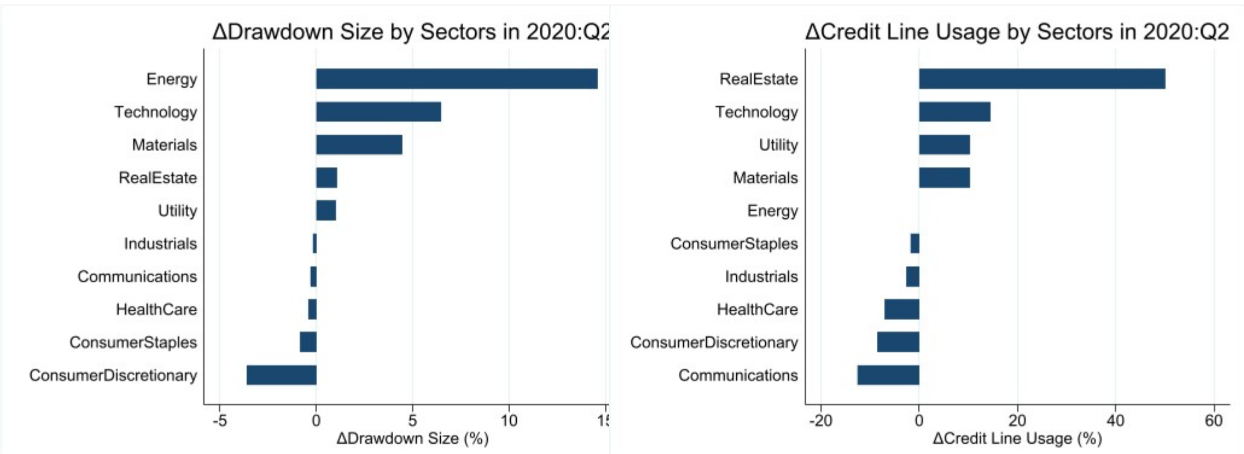


Figure 7. The diagram on the left shows the absolute difference in drawdowns between 2020:Q1-Q2 as a percentage of firms' total assets, whilst the diagram on the right shows firms' credit line utilization difference over the same time period, as a percentage of the firms' total assets.

dustrial 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 *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 (17), 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.[18]

6.1 Work Flexibility and Credit Lines Drawdowns

6.1.1 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:

$$Y_i \quad = \quad \alpha + \beta_1(\textit{Industry Groups}_i \times \textit{2020:Q2}) + \gamma X_i + \epsilon_i \tag{7}$$

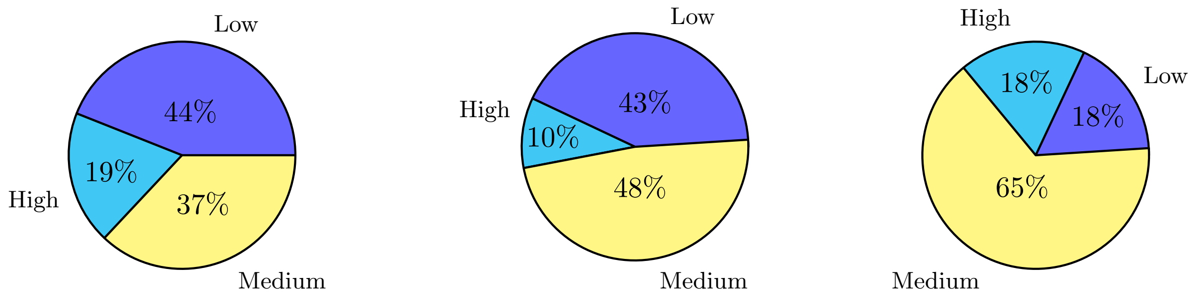
The dependent variable, Y_i, consists of: 1) Credit line usage, equal to the drawn amount relative to the total committed amount of credit lines; 2) Investment, equal to capital expenditure scaled by non-cash assets; and 3) Cash holdings, equal to cash scaled by non-cash assets. The *Industry Groups*$_i$ 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 (18) 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

[18]Note that Table (17) does not contain all the sectors or industries within the BICS. It merely displays the sectors or industry groups of our sampling firms.

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

In a nutshell, there is evidence that European firms used their credit lines for precautionary reasons and not for investment. Panel A in Table (18) shows that over 80% of firms affected by the pandemic, to some extent, drew down their credit lines in anticipation of a liquidity shock. Figure (8) shows that particularly firms within the group mild are the 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), credit lines drawdowns and liquidity management as a new mechanism of firms' financial constraints.



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

Figure 8. 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.

6.2 Empirical Identification

The previous results suggest that social distancing policies (work flexibility) are important to understand firms' expected revenue and panic borrowing. In this section, we use an econometric setting similar to the one used in the previous section (2SLS) to study the effect of work flexibility on expected revenue given the COVID-19 shock. The hypothesis is 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:

$$I(Exposure) = \begin{cases} 1 & \text{if } Exposure \geq 0.75 \\ 0 & \text{if } Exposure \leq 0.3 \end{cases}. \tag{8}$$

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:

$$EBITDA_{i,t} = \delta_0 + \delta_1.I(Exposure) + \eta_{i,t} \tag{9}$$

	(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 18. **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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$Drawdown_{i,t} = \beta_0 + \beta_1 \widehat{EBITDA}_{i,t} + \beta_2 \widehat{EBITDA}_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t}. \tag{10}$$

The first-stage regression in equation (9) 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 (10) shows how EBITDA affects drawdown decisions. $\widehat{EBITDA}_{i,t}$ denotes the fitted value of *EBITDA* from the first-stage regression.

Table (19) 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. We have 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 (19) shows the results from our 2SLS. The coefficient on the interaction ($\widehat{EBITDA}_{i,t} \times \mathit{2020{:}Q2}$) is significant at 10% level, confirming that the inelasticity 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 line drawdowns and cash accumulation.

In Table (20), we study whether banks accommodated credit insurance to all the firms or if they worked with firms according to their degree of work flexibility. In column (1), we consider both exposed and unexposed firms, while in columns (2) and (3), only the exposed and unexposed ones. In column (4), we show the 3-way interaction results and finally, in column (5), the 2SLS results. The empirical results in Table (20) show a negative relationship between cash flow and total credit line size at the peak of the shock in 2020Q2. These results are robust across the different econometric specifications. They suggest that banks worked with the most affected firms at the peak of the COVID-19 shock and provided them with the necessary credit insurance. These results, together with the ones presented in Table (16) (Panel B) are surprising given that Acharya et al. (2013) suggest that shocks increasing aggregate risk are an important determinant of how banks provide liquidity insurance. Clearly, the COVID-19 shock is different from the weather shock studied in Brown et al. (2021), as the latter is exogenous to the firm and fully idiosyncratic. Instead, the shock studied in this paper is also completely exogenous but only partly idiosyncratic (i.e. it is related to the degree of firms' work flexibility). We believe that results in this and previous sections help to better understand how firms manage their liquidity risk. Banks accommodate liquidity insurance following a shock which is unrelated to firms' fundamentals, and although increases aggregate risk, it impacts firms heterogeneously.

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)
$\text{I}(\text{Exposure}_i)$				0.028	
				(0.018)	
$\text{EBITDA}_{i,t} \times \text{I}(\text{Exposure}_i)$				0.450	
				(0.377)	
$\text{I}(\text{Exposure}_i) \times$2020:Q2				0.027*	
				(0.016)	
$\text{I}(\text{Exposure}_i) \times \text{EBITDA}_{i,t} \times$2020:Q2				-1.968**	
				(0.927)	
$\text{Leverage}_{i,t}$	0.083***	0.108***	0.079**	0.086***	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 19. **Credit Lines Drawdowns and EBITDA during the COVID-19 crisis (OLS & 2SLS).** This table shows the results from Equation (10) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	Total Credit Line Size				
	(1) OLS Two Firms	(2) OLS Exposed Firms	(3) OLS Unexposed Firms	(4) OLS 3-Way Interaction	(5) 2SLS Two Firms
$\text{EBITDA}_{i,t}$	-0.188	-0.094	-0.390	-0.532	-2.432***
	(0.139)	(0.156)	(0.406)	(0.361)	(0.692)
$\text{EBITDA}_{i,t}\times$2020:Q2	-1.215**	-1.670***	-0.200	0.264	-0.731*
	(0.513)	(0.606)	(0.869)	(0.732)	(0.438)
$\text{I(Exposure}_i)$				0.029	
				(0.018)	
$\text{EBITDA}_{i,t}\times\text{I(Exposure}_i)$				0.448	
				(0.379)	
$\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**	
				(0.931)	
$\text{Leverage}_{i,t}$	0.082***	0.105***	0.079**	0.085***	0.035
	(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 $\text{CL}_{i,t}$	1.365***	1.416***	1.245***	1.370***	1.366***
	(0.035)	(0.044)	(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	0.713	0.693	0.834	0.716	0.713

Table 20. **Banks' Collaboration with Different Firm Types.** This table shows both the OLS and 2SLS regression results of Equations (9) & (10) with different dependent variables. The dependent variable is total committed credit lines 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 The 2008 Financial Crisis and The 2012 European Crisis

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

6.3.1 Work Flexibility During the 2008 Financial Crisis

Table (21) shows weak empirical evidence that the work flexibility during the financial crisis impacted firms' expected revenue in Europe and drove credit line drawdowns. In a nutshell, work flexibility was not an issue during the 2008 financial crisis. The following 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. **Credit Lines Drawdowns and EBITDA during the 2008 financial crisis (OLS & 2SLS).** This table shows the estimations of Equation (10) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3.2 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 that crisis. These and previous results are new and interesting as they point towards a story where the nature of shocks may matter to understanding firms' liquidity risk management. We are unaware of empirical papers investigating and discussing this critical new issue.

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
$\text{EBITDA}_{i,t}$	-0.081	-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. **Credit Lines Drawdowns and EBITDA during the 2012 European crisis (OLS & 2SLS).** This table shows the estimations of Equation (10) 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Conclusion

Why did European firms draw down credit lines and accumulated cash during the COVID-19 shock? We studied cash flow risk management when firms are hit by a shock unrelated to their fundamentals. We showed that European firms went into a "panic borrowing" and that an unexpected shortfall in revenue drove it 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 to challenges for the same models as they assume credit lines exogenously. That is, credit lines are means to support investment decisions, not to accumulate cash. The panic reported in this paper suggests that firms used credit lines for liquidity accumulation during the COVID-19 shock. We empirically implement a battery of econometric methodologies and quasi-natural experiments to identify the process through which the shock sharply increased firms' demand for credit insurance. Finally, we showed a novel and exciting interplay mechanism between firms' work flexibility (also 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, which banks cannot ignore 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 or others) and, probably, how this risk correlates with firms' idiosyncratic risk. These are important and new topics for theoretical and empirical research, which we leave for further 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 shocks and the negative externalities for society from the run on banks' credit lines.

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Appendices

A Description of Variables

Table A23. **Description of Variables**

Variable	**Description**
Capital Expenditure	Amount the company spent on purchases of tangible fixed assets. Note that capital expenditure is taken its absolute value. Source: Bloomberg.
Cash Holdings	Cash in vaults and deposits in banks. Include short-term investments with maturities of less than 90 days. May include marketable securities and short-term investments with maturities of more than 90 days if not disclosed separately. Exclude restricted cash. Source: Bloomberg.
EBITDA	Net income with interest, taxes, depreciation, and amortization, which is also known as EBITDA. EBITDA is commonly used as the measurement of cash flow by commercial banks to set various types of covenants on lines of credit. Source: Bloomberg.
Credit Line Usage	The drawn amount of credit lines divided by the total committed amount. Source: Bloomberg.
Credit Ratings	An indicator for each rating class based on S&P Issuer Rating, such as *AAA-A*, *BBB* or *Non-IG*. Source: Bloomberg.
Drawdowns	Amount of the credit line that is currently used, equivalent to the total lines of credit less the undrawn credit lines. Source: Bloomberg.
Leverage	The total amount of debt relative to assets. Source: Bloomberg.
Log(Asset)	The natural logarithm of total assets. Total assets include the total of all short and long-term assets as reported on the Balance Sheet. Source: Bloomberg.
Price-to-Book Ratio	Ratio of the stock price to the book value per share. Source: Bloomberg.
Short-Term Debt	Include bank overdrafts, short-term debts and borrowings, repurchase agreements (repos) and reverse repos, short-term portion of long-term borrowings, current obligations under capital (finance) leases, current portion of hire purchase creditors, short-term operating lease liabilities after the adoption of International Financial Reporting Standards (IFRS) 16 and Accounting Standards Codification (ASC) 842, trust receipts, bills payable, bills of exchange, bankers acceptances, interest bearing loans, and short term mandatory redeemable pref-ferred stock. Net with unamortized premium or discount on debt and may include fair value adjustment of embedded derivatives. Source: Bloomberg.
Tangible Assets	Total assets minus intangible assets. Source: Bloomberg.
Net Income	Amount of profit the company made after paying all of its expenses. Source: Bloomberg.
Undrawn CL	Total remaining amount of committed credit line that a bank or financial institution has agreed to lend at the period end date. Source: Bloomberg.
Undrawn Capacity	The ratio is equal to 1 minus credit line usage, representing the remaining percentage of committed credit line. Source: Bloomberg.

B Firms' Solvency and Liquidity Constraints

B.1 Solvency-Driven Credit Line Draw downs

This appendix empirically studies the association between solvency risk and firms' decisions to draw down credit lines. We also highlight the substitution effect between internal resources (cash holdings) and external ones (credit lines) in solvency constraints. We do it for 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), for the US, show that 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 financial constraints, high-cash holdings firms behave the same way as low-cash holdings 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 (A24) shows an example of a corporate balance sheet. The left-hand side shows total assets and contains cash, cash equivalent, and risky investment.[19] The right-hand side shows the liabilities 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 A24. 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 (A24), total assets, cash and cash equivalent, risky investment, debt, and equity should simultaneously satisfy the balance sheet equation below:

$$C + I = D + E$$

To study firm's behaviour in response to solvency risk following an unexpected shock to the risky

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

investment, we consider the following solvency condition showing 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 assumes that firms remain 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 have

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

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 this expression as:

$$\frac{R_I}{R_D} = 1 - \frac{E}{A - C} \tag{11}$$

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 name 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 RID falls, less return on risky investment is needed to compensate for debt. Therefore, a fall of the RID means that 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:

$$\begin{aligned} Drawdown_{i,t} &= \alpha + \beta_1 RID_{i,t-1} + \beta_2 (RID_{i,t-1} \times \mathit{2020{:}Q2}) \\ &\quad + \gamma X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{12}$$

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

$$RID = 1 - \frac{\mathit{Book\ Value}}{\mathit{Total\ Assets} - \mathit{Cash\ \&\ Cash\ Equivalent}} \tag{13}$$

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 (A25) shows the results. Columns (1) to (4) in Table (A25) show that the coefficient on RID, β_1, is statistically significant and positive for the full sample. Higher insolvency risk is associated with higher credit line drawdowns. However, there is a shift in the sign of the coefficient if we consider the interaction coefficient, $RID_{i,t-1} \times \mathit{2020{:}Q2}$. 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 seems to suggest a negative association between credit line drawdowns and solvency risk.[20] Finally, it is indicative the insignificant coefficients in 2020Q3 as they imply that the effect of the shock on firms was only significant at the peak of the COVID-19 shock (2020Q2) but did not extend to 2020Q3. In a nutshell, lower-risk firms drew down credit lines in 2020:Q2.[21]

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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

Table A25. **RID Ratio and Drawdowns (Euro Area)** This table shows the results of the baseline models in equation (12) 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 credit lines usage. 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 for the whole sample (*All Firms*) and three subsamples (*Low-*, *Medium-*, and *High-Risk Firms*). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A9. 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.

B.2 Credit Ratings and Credit Lines Drawdowns

In Appendix B.1, we showed that, over the whole sample, there is a positive and significant association between firms' solvency risk and credit lines drawdowns, but this relationship changed in

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

[21]We also include cash holdings as a control variable which has a significant and positive coefficient. Results are available in the Online Appendix

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. We now replace our measure of firms' solvency with credit ratings and consider changes in firms' credit risk over three quarters (Q1 - Q3), before and after the COVID-19 shock (2020:Q2) and credit line drawdowns.

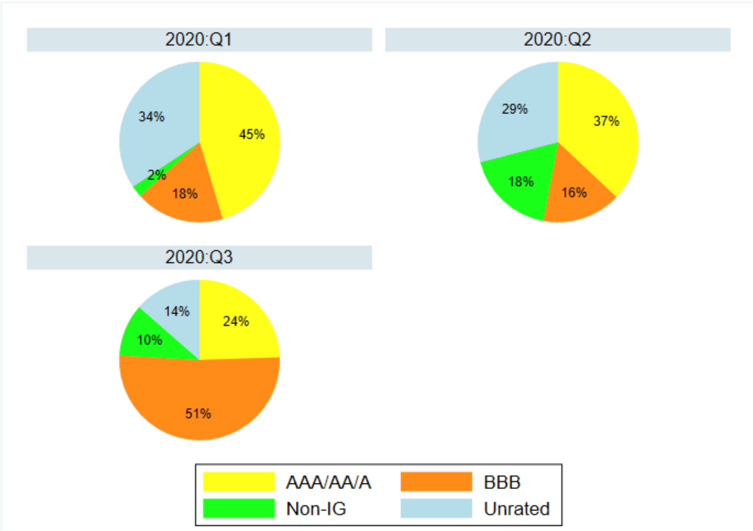

Figure A10. This diagram shows the distribution of credit line drawdowns across credit ratings during 2020:Q1 - Q3.

Figure (A10) sheds further 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" phenomena (i.e. firms whose credit rating is quickly deteriorating due to COVID-19 shock) is not specific to the US. However, it extends to the European market, implying a more substantial degree of international corporate market integration. Overall, Figure (A10) is consistent with our previous results showing a negative association between firms' solvency risk and credit line drawdowns at the peak of the COVID-19 shock.

B.3 Liquidity Constraints and Credit Lines Drawdowns

In this appendix, we show that our firms are also (on average) good firms in terms of liquidity. Sufi (2009) shows that profitable firms rely more on credit lines as high cash is critical to satisfying covenants. 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 use the indicator developed by Bosshardt & Kakhbod (2020):

$$\text{Distress}_t = \frac{\text{Short-term Debt}_t - \text{Cash \& Cash Equivalent}_t - \text{Net Income}_t}{\text{Total Assets}_t} \tag{14}$$

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.

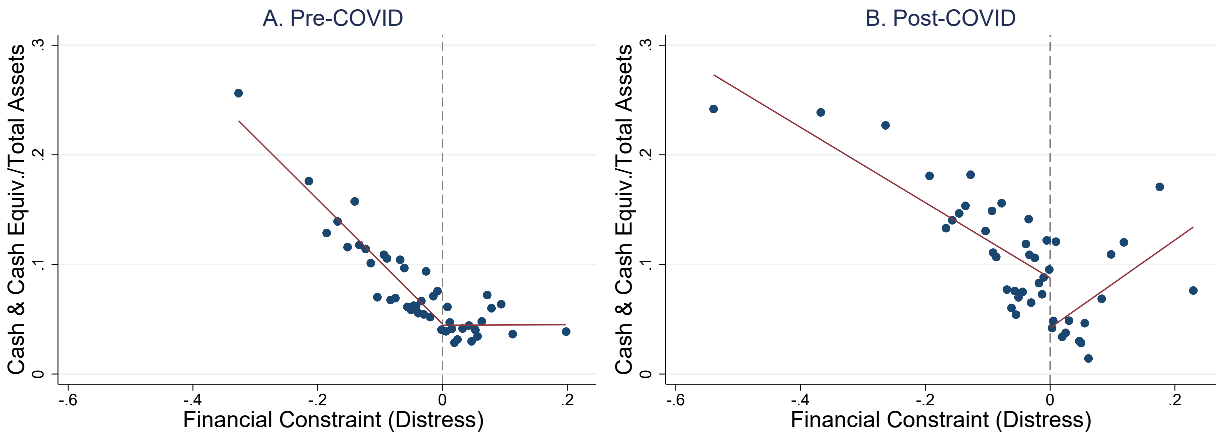

Figure A11. The diagram on the left-had-side shows a regression-discontinuity design (RID) of cash and cash equivalents against financial constraint (distress) before COVID. The horizontal axis shows the distress ratio, and the vertical axis shows the cash and cash equivalents relative to total assets. The diagram on the right shows the RID after the pandemic outbreak. In addition, the horizontal axis presents the distress, and the vertical axis presents the cash and cash equivalents scaled by total assets.

Figure (A11) 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:

$$Drawdown_{i,t} = \alpha + \beta_1 Distress_{i,t} + \beta_2 Distress_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t} \tag{15}$$

where the notations and controls are defined earlier.

Table (A26) 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 this 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 up cash holdings in 2020:Q2, while there insignificant evidence that this also continued after 2020Q2.

In Figure (A12), 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 why.

Firstly, we do not find a substitution effect as in Campello et al. (2011) for European firms during the COVID-19 shock. Instead, our results 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 following 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)
Distress$_t \times$2020:Q1		-0.162	-0.144		-0.234	-0.163
		(0.138)	(0.139)		(0.422)	(0.423)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.031	0.032	0.021	0.016	0.020
Panel B: 2020:Q2						
Distress$_t$	0.095***	0.139***	0.240***	0.200***	0.187*	0.417***
	(0.025)	(0.035)	(0.047)	(0.070)	(0.103)	(0.133)
Cash Holdings$_t$	0.084		0.218***	0.333**		0.531***
	(0.057)		(0.067)	(0.169)		(0.198)
Distress$_t \times$2020:Q2		-0.097**	-0.188***		-0.076	-0.283*
		(0.044)	(0.052)		(0.126)	(0.148)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.035	0.047	0.021	0.016	0.024
Panel C: 2020:Q3						
Distress$_t$	0.095***	0.081***	0.096***	0.200***	0.131**	0.194***
	(0.025)	(0.022)	(0.025)	(0.070)	(0.064)	(0.070)
Cash Holdings$_t$	0.084		0.080	0.333**		0.354**
	(0.057)		(0.057)	(0.169)		(0.170)
Distress$_t \times$2020:Q3		-0.102	-0.082		0.299	0.390
		(0.128)	(0.129)		(0.368)	(0.370)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	804	804	804	788	788	788
Adjusted R^2	0.032	0.030	0.031	0.021	0.017	0.021

Table A26. **Drawdowns and Liquidity Distress**. This table shows the results of the baseline models in equation (15). The dependent variable in columns (1) to (3) is credit line drawdowns scaled by total assets. The dependent variable in columns (4) to (6) is credit lines usage. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between distress and time dummies (*2020:Q1-Q3*). Panel A shows the interaction between distress and *2020:Q1*. Panel B shows the interaction between distress and *2020:Q2*. Panel C shows the interaction between the and *2020:Q3*. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

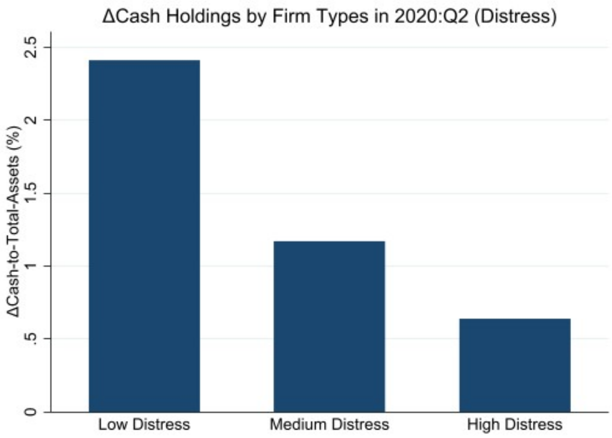

Figure A12. The diagram shows the changes in cash holdings in 2020:Q2, equivalent to the current scale less the previous one, against different firm types based on financial constraint (distress). The horizontal axis shows three types of firms: Low Distress (25%), Medium Distress (50%) and High Distress (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.

C RID

In this Appendix, we provide additional support to the results in Appendix B and in Section 3 and use alternative specifications where the firms' indicators are constructed according to their ratios to total assets. Results are reported in the tables below and show that our firms are financially unconstrained.

	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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Firms	Low Risk	Medium Risk	High Risk	All Firms	Low Risk	Medium Risk	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)
$\text{Distress}_t \times$2020:Q2	-0.175***	-0.266**	0.186	0.304	-0.276**	-0.937***	0.840	0.683
	(0.050)	(0.127)	(0.434)	(0.235)	(0.127)	(0.317)	(1.155)	(0.662)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	804	239	418	146	788	231	413	143
Adjusted R^2	0.044	0.068	0.021	0.455	0.025	0.067	0.028	0.192

Table 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 provide additional empirical identification results using a different econometric setting and following Malenko & Shen (2016), we show that following the COVID-19 shock, firms' earnings and work flexibility (i..e degree of exposure to the COVID-19 shock) are important to understand the demand of liquidity insurance:

$$\begin{aligned} Drawdown_{i,t} \quad = \quad & \beta_0 + \beta_1 EBITDA_{i,t} + \beta_2 BelowCutoff_{i,t} + \beta_3 EBITDA_{i,t} \times \mathit{2020{:}Q2} \\ & + \beta_4 BelowCutoff_{i,t} \times \mathit{2020{:}Q2} + \beta_5 BelowCutoff_{i,t} \times EBITDA_{i,t} \\ & + \beta_6 BelowCutoff_{i,t} \times EBITDA_{i,t} \times \mathit{2020{:}Q2} + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{16}$$

where

$$BelowCutoff_t = \begin{cases} 1 & \text{if } Free\ Cash\ Flow_t \in [-\lambda, 0) \\ 0 & \text{if } Free\ Cash\ Flow_t \in [0, \lambda] \end{cases} \tag{17}$$

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 (A13) shows the individual drawdown effects based on equation (2) 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 (A14) shows the same effect based on the results in Table (D1).

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 D1. **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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

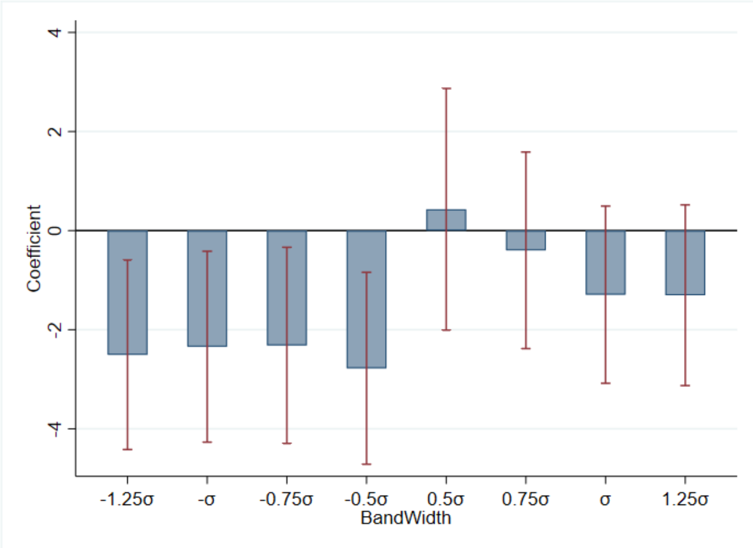

Figure A13. The diagram shows the estimated percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. The horizontal axis shows several bandwidth selections. Each value computed on the vertical axis is 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.

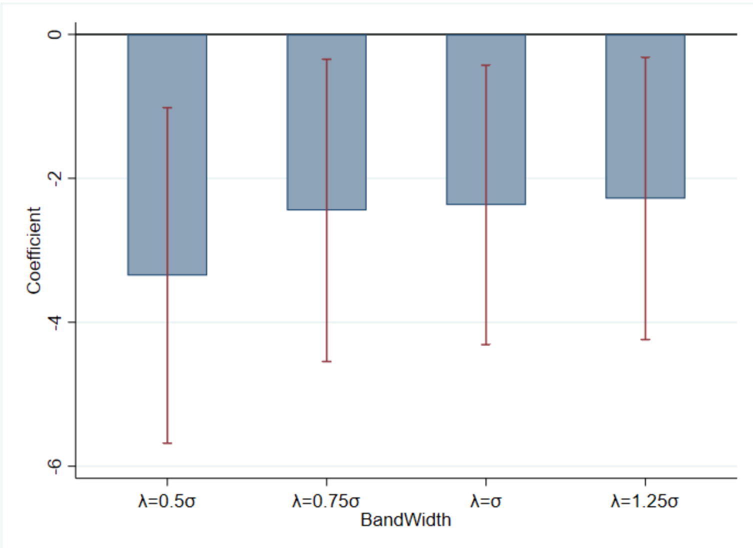

Figure A14. The diagram shows the estimated cross-sectional differential percentage point changes in the draw down to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in draw 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.