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The Determinants and the Real Effect of Credit Line: Evidence from Europe

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Abstract

This PhD thesis comprises four chapters that collectively investigate firms' credit line utilisation and liquidity risk management in the context of the COVID-19 shock. Each chapter addresses distinct aspects of this topic, providing valuable insights into the behaviour of European firms and the implications for firm value generation.

Chapter 1 starts with an overview of what credit line is and what we know about it from the COVID-19 shock in the European context.

Chapter 2 focuses on firms' liquidity risk management during the unprecedented COVID-19 shock. While existing literature extensively covers credit line usage in normal circumstances, this study explores firms' responses to an exogenous shock unrelated to their fundamentals. By building upon previous research on weather shocks, the chapter demonstrates that the COVID-19 shock led to panic borrowing by financially unconstrained European firms. Drawing down credit lines became a means to mitigate the sharp decline in expected cash flow. The analysis reveals significant heterogeneity in borrowing behaviour across countries and industries, highlighting the importance of firm exposure to the shock. Moreover, the chapter highlights the policy implications of banks supplying credit insurance during periods of heightened aggregate risk.

Chapter 3 investigates the purposes of credit line utilisation by European firms during the COVID-19 shock. With a focus on the European market, the chapter fills the gap in the literature by examining the factors that drive firms to access credit lines. The empirical analysis reveals that low-quality and non-investment-grade firms were more likely to draw down credit lines to mitigate cash flow shortfalls caused by the pandemic. Additionally, the study investigates whether firms used credit lines for precautionary savings or funding investment. The findings indicate that credit line drawdowns were driven by firms' precautionary motives rather than investment funding. The chapter also explores the sensitivity of credit lines to firm size, demonstrating that medium-sized firms were more affected by cash flow shortfalls and drew down credit lines to a greater extent. Moreover, the unique nature of the COVID-19 crisis is established by comparing it with the European Crisis, where little evidence supports the precautionary

purpose.

In Chapter 4, the thesis presents a comprehensive model that examines the optimal capital structure, investment decisions, and implications of credit line utilisation for wealth generation. The model highlights the significance of balancing the benefits and costs of credit line usage. It considers factors such as borrowing costs, cash holdings, line commitments, and covenant restrictions in shaping firms' liquidity management strategies. Through a combination of theoretical analysis and empirical estimation using firm-level data, the chapter provides insights into the association between risky assets, productivity, and revolving credit facility utilisation. The findings demonstrate that credit lines play a crucial role in enhancing firm value through aggressive investment and flexible liquidity management. However, the excessive use of credit lines can lead to diminished firm worth. The analysis further shows the negative impact of the COVID-19 pandemic on corporate productivity and explores the effects of labour factors during the pandemic-induced lockdown.

In conclusion, this PhD thesis contributes to the understanding of firms' credit line utilisation and liquidity risk management, particularly in the context of the COVID-19 shock. The chapters shed light on the behaviour of European firms, the factors driving their demand for credit lines, and the implications for firm value generation. The findings have important policy implications, emphasising the role of banks in supplying credit insurance during periods of heightened aggregate risk. Overall, this thesis enhances our knowledge of firms' responses to shocks and their strategies for managing liquidity risk, providing valuable insights for both academia and practitioners in the field of finance.

Dedication

"Though a decade has passed since my beloved grandmother left this world, her spirit and the lessons she taught me continue to guide and inspire my journey. In loving memory, this work is dedicated to her."

Declaration

"I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution."

Printed Name:

Signature:

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Chapter 1

Literature Review

1.1 Credit Line and Short-Term Liquidity Risk Management

Credit lines have facilitated a notable inflow of credit from financial institutions to European businesses over the last ten years. Our calculations indicate that European enterprises (specifically those within the euro area) swiftly accessed more than €87 billion in a concise period to maintain their financial stability. This marked an unprecedented shift towards liquidity on a macroeconomic level, coinciding with a surge in average ratios of credit lines to total assets – increasing from 4.72% during the first quarter of 2020 to 5.15% in the second quarter of 2020, with an average of 7.00% spanning the second and third quarters of 2020. Comparable outcomes are demonstrated by Acharya et al. (2020) in the context of US firms.

The existing literature primarily examines how firms manage liquidity risk through credit lines (e.g., Campello et al. (2011) and Acharya et al. (2012), among others cited later). However, this thesis addresses a relatively unexplored aspect: how firms handle liquidity risk when confronted with an unforeseen shock, such as COVID-19, that is entirely external to their fundamental characteristics and affects specific firms idiosyncratically. In this context, my research is closely aligned with the work by Brown et al. (2021), who investigate short-term liquidity risk management during weather-induced shocks. I extend and adapt their framework to the distinct circumstances of the COVID-19 shock. It's important to note that these two shocks differ significantly in their potential impact on overall risk, marking a significant departure from Brown et al. (2021). For instance, research by Acharya et al. (2013) demonstrates that shocks amplifying aggregate risk can curtail firms' access to credit insurance. My objective is to establish that variations in firms' cash flow result from the COVID-19 shock rather than shifts in their long-term profitability or fundamental characteristics.

This thesis demonstrates that financially unconstrained European firms, during the peak of the COVID-19 shock, entered a state characterized as "panic borrowing," promptly utilizing credit lines following a substantial decline in projected cash flow. This outcome is observed not only at the firm level but also across national and industry levels. Expanding the analysis to encompass country and industry dimensions allows us to explore whether variations in firms' exposure to the COVID-19 shock impact their liquidity risk management. The thesis underscores the diversity among borrowers, indicating that firms highly exposed to the COVID-19 shock within affected countries and industries accessed credit lines and amassed cash reserves. These novel findings complement recent research on firms' credit line utilization during the COVID-19 shock (Acharya et al. 2020) while introducing a novel risk factor: the flexibility of the workforce and country policies.

This thesis also carries significant policy implications and aids in comprehending how businesses manage their liquidity when confronted with shocks unrelated to their foundational factors. For instance, Acharya et al. (2013) demonstrate that shocks heightening aggregate risk can impact the availability of credit insurance. During the COVID-19 shock, banks provided the requested credit insurance, assisting enterprises more susceptible to this shock in navigating their short-term liquidity risk. Our empirical findings, combined with the extensive literature on the 2008 financial crisis, underscore the significance of the nature of the shock in explaining both why firms tap into their credit lines and how banks decide to furnish credit insurance.

Credit lines represent financial agreements that permit businesses to access funds from their bank accounts, providing them with readily available funding as a precautionary measure to counteract unforeseen shocks. Consequently, these lines of contingent liquidity function as a form of insurance against unanticipated future liquidity needs. Given the substantial reliance of European enterprises on bank-centred funding, credit lines hold particular significance in Europe. This underscores their importance compared to alternative capital market-based financing methods in the United States. In this context, our examination of European companies complements research focused on the US market (e.g., Acharya et al. (2020)) by investigating international financial and corporate market integrations, as highlighted in Berg et al. (2017)'s work.

Much research exists regarding credit insurance and firms' liquidity risk management. This research predominantly relies on theoretical frameworks presented by Shockley & Thakor (1997) and Holmström & Tirole (1998), who propose that credit lines, distinct from debt, act as credit insurance, enabling firms to secure credit when it is most crucial. These models primarily focus on endogenous shocks arising from poor managerial choices.

One of the initial empirical investigations can be found in Sufi (2009). This study examined the interplay between internal resources (cash reserves) and external sources (credit lines) before the 2008 financial crisis, characterized by ample credit availability. Sufi's research revealed a tendency for profitable firms to utilize credit lines, while those without profitability encountered challenges accessing credit through this channel when it was most crucial. The study operates under the assumption that endogenous shocks, such as poor managerial decisions, drive demand for credit insurance. In complement to the findings of Sufi (2009), Acharya, Almeida, Ippolito & Perez (2014*b*) shed light on why banks retract credit lines from unprofitable firms. Their research underscores how banks employ covenants to monitor firms' liquidity management. Consequently, it is inferred that firms utilizing credit lines exhibit lower liquidity risk compared to those relying on cash reserves. Our contribution extends these findings in various dimensions. Initially, we consider an entirely exogenous shock and employ an empirical identification strategy to confine our analysis to short-term liquidity risk management. Lastly, we furnish robust empirical proof of collaborative behaviour between banks and firms amid the COVID-19 shock.

Campello et al. (2011), utilizing data from the 2008 financial crisis and US corporations, illustrate a substitution phenomenon between cash reserves and credit lines when firms confront acute credit scarcity. Their findings indicate that firms possessing greater internal funds exhibit reduced reliance on credit lines, even if these lines offer lower costs. Amid the 2008 crisis, Ivashina & Scharfstein (2010) observed borrowers tapping into credit lines for precautionary motives. To expand and enhance these investigations, we encompass the COVID-19 shock, revealing that financially less constrained firms urgently sought cash during the COVID-19 period. Furthermore, we demonstrate that the "panic borrowing" evident in US firms during the 2008 crisis (Campello et al. 2011, Ivashina & Scharfstein 2010) does not translate to European enterprises.

More recently, a segment of the scholarly discourse has emerged concerning firms' liquidity risk management amidst the COVID-19 crisis. While the research by Halling et al. (2020) investigated diverse financing approaches, mainly bonds and equity, adopted in the US during the pandemic, Schivardi et al. (2020) delved into the phenomenon of zombie lending in the same period. Analyzing the UK context, Calabrese et al. (2022) examined the impact of government support on medium-sized enterprises (SMEs) during the COVID-19 shock. While these cited studies significantly contribute to our comprehension of firms' responses to the COVID-19 shock, such as venturing into new markets and the role of government support, their relevance to this thesis remains limited.

A relevant paper concerning this thesis is Acharya et al. (2020). This study demonstrates that in March 2020, US firms extensively utilized their credit lines for borrowing substantial funds. Moreover, it reveals that, particularly at the initial stage of the period, these credit line users were firms facing fewer constraints. Our work both complements and extends these findings through various avenues. The advent of the COVID-19 shock prompted a unified policy response across Europe, necessitating a degree of consistency (referred to as country flexibility). Notably, social distancing measures varied considerably among European nations. Did this divergence in social distancing policies contribute to the phenomenon of "panic borrowing"? Our study addresses this pivotal question, which prior research has not explored. By incorporating infection rates across Europe and employing a proxy for a country's social distancing policy (Oxford Stringency Index), we underscore the significance of country flexibility. Our analysis indicates that firms in countries with higher COVID-19 infection rates and stricter policy measures exhibited "panic borrowing," opting to draw down their credit lines.

We adopt the concept of work flexibility as explored in Campello et al. (2020) to fully leverage variations among countries and industries. Their findings highlight the necessity of work flexibility in comprehending job hiring patterns during the COVID-19 era in the US. This adaptability also holds importance in deciphering firms' behaviours like "panic borrowing." Furthermore, we establish that work flexibility's relevance is specific to the COVID-19 crisis and does not extend to the 2008 financial crisis or the 2012 European crisis. Overall, our outcomes indicate that comprehending 1) the observed "panic borrowing" during COVID-19 and 2) the differential collaboration between banks and firms across countries and industries requires considering the nature of the shock and the diversities present. These contributions supplement the insights of Acharya et al. (2020) for the US. While acknowledging that our findings only capture a portion of the events in March 2020, omitting factors like government interventions and cross-country cultural disparities, our empirical evidence remains significant as it generates novel avenues for theoretical and empirical research in the future. We intend to address these aspects in our upcoming agenda.

Additionally, we note a relevant literature thread that emerged early in the COVID-19 shock. This work explores the correlation between COVID-19-related shutdowns, employment opportunities, and emerging markets. For instance, Kogan et al. (2020) discerns that industries with limited remote work options experienced more substantial declines in employment, anticipated revenue growth, and stock market performance. Conversely, Barrero et al. (2020) and Hassan et al. (2020) reveal how certain firms capitalized on the shutdowns to bolster investments in new markets. Our contribution complements this literature by centring on firms' liquidity management in March 2020 and the intricate interplay between firms and banks regarding credit insurance demand and supply.

Lastly, this thesis contributes to the expanding and contemporary literature concerning the impact of natural incidents and the COVID-19 pandemic on the management of firms' liquidity risk (Koetter et al. 2020, Verbeke 2020, Brown et al. 2021, Calabrese et al. 2022, Sun et al. 2022). Our work supplements these inquiries by offering additional insights into their findings and the potential implications for banking institutions. To illustrate, Sun et al. (2022) establish compelling evidence linking lower cash reserves with firm financial hedging activities. Our empirical analysis introduces the undrawn credit line variable as a control measure, representing a hedge against liquidity shocks. This variable consistently holds a positive and statistically significant coefficient, suggesting that firms employ credit lines to hedge liquidity risk rather than relying solely on cash reserves.

1.2 Credit Line, Credit Risk, and Cash Holdings

Was the impact of the COVID-19 crisis distinct for businesses utilizing bank credit lines? On one side, scholarly literature emphasizes the significance of credit lines as a crucial financing source for corporate investments (Holmström & Tirole 2000, Campello et al. 2012, Berrospide & Meisenzahl 2015). Particularly in the context of the COVID-19 shock, research by Li et al. (2020) and Greenwald et al. (2021) for the US market reveals that companies utilized credit lines to bolster their investments. Conversely, Bosshardt & Kakhbod (2020) and Acharya & Steffen (2020*b*), also focusing on the US market, contend that firms drew from credit lines as a precautionary measure. However, the scope of literature concerning the European market remains limited, despite European nations being categorized as "bank-based economies," establishing the relevance of credit lines concerning corporate cash holdings and investment (Campello et al. 2012). This thesis aims to comprehend the motives of European firms for resorting to credit lines in the face of the COVID-19 shock. Did riskier firms escalate their credit line drawdowns more than stable ones during the pandemic? Did businesses tap into credit lines for precautionary savings or to fund investments? Was liquidity management contingent on firm size? Was the impact of the pandemic on firms' liquidity management strategies distinctive? These inquiries form the basis of our investigation in this thesis.

We demonstrate that in the second quarter of 2020 (2020:Q2), companies accessing credit lines were of lower quality and categorized as Non-Investment Grade (Non-IG) firms. This observation aligns with patterns observed in the US market during the pandemic (Acharya & Steffen 2020*b*) and the European market during the Global Financial Crisis (Campello et al. 2012). Given the shock induced by the pandemic, firms facing higher short-term credit risk tapped into credit lines gradually to counter their cash flow deficits. Beyond credit ratings, we create an alternative gauge for short-term credit risk known as the exposure-at-default ratio (EAD). Firms with greater EAD (indicating higher credit risk) made more substantial credit line withdrawals, particularly in response to the pandemic shock. Categorizing firms as high-risk or low-risk based on EAD, we observe that high-risk firms increased their credit line utilization by 41.4%. In contrast, low-risk counterparts conversely reduced theirs by 39.8% during the sampling period. Our empirical findings support that credit risk was pivotal in driving the demand for credit lines amid the pandemic-induced shock.

We examine whether firms utilized credit lines for precautionary saving or investment intentions. Employing cash and cash equivalents and capital expenditure as indicators of cash saving and investment, respectively, we demonstrate that credit line withdrawals did not correlate with heightened investment levels. Instead, they stemmed from companies' precautionary strategies to counteract an increase in short-term credit risk. We also address the endogeneity issue arising from the reciprocal influence between credit line choices and cash saving or investment funding decisions. Therefore, our empirical approach relies on exogenous variations prompted by the firm's unused credits and prior cash holdings. These serve as instruments to mitigate the endogeneity concern between present cash and credit line determinations. Particularly during the pandemic shock, we observe the significance of this issue.

Subsequently, our investigation delves into the responsiveness of credit lines based on company sizes. A study by Guney et al. (2017) underscores that during crisis periods, smaller, financially constrained enterprises tend to rely heavily on revolving credit facilities instead of their larger counterparts. The use of credit lines for investment by small businesses was notable during the 2007-2009 and European crises. Drawing inspiration from Guney et al. (2017), we categorize firms into three groups based on their total assets: small, medium, and large. Our findings reveal a noteworthy pattern – medium-sized firms exhibited a heightened sensitivity to cash flow shortages compared to the other categories. This sensitivity translated into a higher frequency of credit line utilization throughout the COVID-19 Crisis.

We proceed to examine the potential influence of company size on credit lines. Guney et al. (2017) observe that smaller financially constrained businesses leaned more heavily on revolving credit facilities than larger counterparts during crises. Small firms utilized credit lines to fund investments amid the 2007-2009 and European crises. Building upon the insights from Guney et al. (2017), we categorize firms based on their total assets into small, medium, and large groups. Our findings reveal that medium-sized firms exhibited a greater sensitivity to cash flow shortages than the other groups, leading to increased credit line utilization during the COVID-19 crisis. Besides, medium-sized enterprises employed credit line drawdowns to accumulate more cash than their counterparts. We also assess whether firms of varying sizes, particularly smaller ones, accessed credit lines to bolster investments amid the COVID-19 Crisis. The evidence challenges the notion that small firms' dependence on credit lines for investment aligns with the context of the pandemic.

We replicate our examination of the pandemic's impact, focusing on the European Crisis (2009:Q4 - 2013:Q4), to explore whether precautionary saving patterns persisted during this period. Identifying the shock period within the Crisis as 2012:Q3, coinciding with the European Central Bank's announcement of the Outright Monetary Transactions (OMT), we assess the validity of precautionary measures. Contrary to the distinctive characteristics of the COVID-19 crisis, our results suggest limited evidence supporting the precautionary intent during the European Crisis. Additionally, an inverse correlation between credit line drawdowns and investment emerges from our analysis, providing an alternative verification form.

This thesis makes dual contributions to the existing literature. Firstly, it extends the current exploration into the impact of the COVID-19 pandemic on the corporate sector. Secondly, it adds to the knowledge base surrounding the precautionary motive. While most COVID-19 research focuses on US firms, there remains a lack of understanding concerning European companies. In March 2020, the European Central Bank (ECB) initiated a program to purchase private and public securities, simultaneously relaxing collateral eligibility rules and providing financial assistance to companies (Didier et al. 2021). Numerous working papers, including Altavilla et al. (2021), Cascarino et al. (2022), and Jiménez et al. (2022), delve into European countries' public guarantee schemes for supporting corporate borrowing. However, these papers are country-specific and offer limited insight into firm characteristics. On the supply side, Dursun-de Neef & Schandlbauer (2021) examine how European banks responded to the COVID-19 shock, adjusting their lending to firms. Their study covers non-financial firms across the Euro Area and sheds light on the impact of the COVID-19 crisis on European firms' liquidity management, encompassing credit lines and cash holdings.

A substantial body of literature underscores the presence of a precautionary motive for holding cash (Almeida et al. 2004, Bates et al. 2009, Eisfeldt & Muir 2016, Acharya & Steffen 2020*b*). Acharya et al. (2012) reveal that examining the precautionary motive for utilizing credit lines may yield misleading outcomes due to the endogeneity of cash holdings in relation to credit risk. They demonstrate that some highly creditworthy firms might exhibit behaviours akin to more financially constrained firms (lower credit quality firms) in their decisions to access credit lines, particularly during periods of ample credit availability. The unique and unpredictable nature of the COVID-19 shock offers a natural laboratory for investigating the financing behaviour of financially constrained firms, given its inherent capacity to exogenously elevate firms' credit risk (Acharya & Steffen 2020*b*). In this context, we further contribute to this literature by empirically testing certain predictions of the Acharya et al. (2012) model while also controlling for two critical factors: the impact of the COVID-19 shock and the context of European firms.

1.3 Credit Line Modelling

This thesis presents a comprehensive framework for generating firm value based on two fundamental factors. Initially, a company possesses internal capital derived from shareholder investments and augments its resources by accessing external funds through bank credit lines. Subsequently, the firm retains a portion of its total funds within its bank account while allocating the remaining portion towards investments in higher-risk assets. This model is designed to determine the optimal capital structure and investment choices, with implications for credit line demand.

Utilizing a calibrated representative firm, we illustrate the advantages of credit lines in enhancing wealth creation. When a firm allocates 75% of its funds to risky assets, an increase in credit line utilization from 21% to 71% results in a noteworthy 13% surge in its value. Excessive reliance on credit lines (e.g., expanding usage to 100%), however, could lead to a 2% decrease in firm value. This underscores that credit lines offer more than a mere substitute for cash holdings, as observed in the existing literature (e.g., Lins et al. (2010)).

Central to our analysis is the importance of capital structure. Theoretical research emphasizes using credit lines to generate assets and safeguard against liquidity shortages (e.g. Boot et al. 1987, Holmström & Tirole 1998, Acharya, Almeida, Ippolito & Perez 2014*a*). Limited literature addresses drawdown repayment (e.g. Nikolov et al. (2019), Cooperman et al. (2023)). We underscore the role of corporate solvency in optimizing wealth. Another key element in our model is cash hoarding. During the COVID-induced recession, credit line drawdowns primarily secured cash (Acharya & Steffen 2020*b*). In simpler terms, firms held substantial drawdowns in bank accounts instead of directing them toward investments. Despite incurring significant opportunity costs, the appeal of maintaining cash appeared more compelling. Hence, we analyze the balance between retaining cash and financing investments. Specifically, by jointly assessing these factors, our model predicts an average increase of 5.5% in the calibrated firm's net worth in relation to credit line utilization.

In the financial intermediation model proposed by Allen et al. (2015), the assumption is that banks fund their investment in a risky technology using both deposits and equity. Their central objective is maximizing the net return on investment after accounting for deposit payments and the opportunity cost faced by shareholders when contributing capital. Consequently, the investment choice becomes intertwined with the company's ability to repay debt and the value of shareholders' equity, aligning the interests of both creditors and shareholders. It is worth noting that existing literature typically treats deposits merely as a form of debt held by banks Diamond (1984).

In our approach, we transpose the challenges of deposit payments for banks into issues surrounding a firm's debt repayment. Additionally, the firm can mitigate capital costs by reserving a portion of funds within its bank deposit account, as explored by (Holmström & Tirole 1998, Acharya, Almeida, Ippolito & Perez 2014*a*), and others.

We start with a straightforward illustration: a company funds its operations using shareholder equity and bank credit lines, then invests these funds into safe assets (cash holdings) and more precarious ventures. With constant equity capital and a specific credit line commitment, managers have the authority to determine the drawdown's extent and the distribution of total funds. When we grant the firm the option to use credit lines without incurring borrowing expenses, we demonstrate that it can enhance its value by adopting a bolder investment approach and mitigate the risk of default by employing a more adaptable liquidity management strategy.

Next, we formulate an intricate foundational model encompassing the firm's efficiency, risk-free return, and borrowing expenses. Within this framework, the firm confronts the trade-off between capitalizing on credit lines' advantages and bearing their associated costs. As for benefits, withdrawals can supply funds for lucrative investments, while unutilized lines offer adaptable liquidity for future needs, as exemplified by Nikolov et al. (2019). However, both active and dormant credit lines entail explicit expenses, including interest payments on withdrawals based on loan rates and commitment fees on unused portions, as detailed in Berg et al. (2016). Consequently, the framework encapsulates the firm's internal operations alongside external economic circumstances. We establish that, at equilibrium, firms can stockpile more cash when credit line costs are high or decrease drawn amounts when investment goals are lofty.

We expand the model across various dimensions that necessitate distinct responses from the calibrated representative firm. In order to move closer to reality, we introduce variability in borrowing costs, resulting in a counteractive relationship between corporate profit and cost. When borrowing costs rise, the firm's tendency to utilize the undrawn balance diminishes, assuming a fixed investment level—an observation in line with recent research (Cooperman et al. 2023). Alternatively, if the firm maintains a constant level of credit line usage, it pursues higher returns on risky assets to enhance repayment. Despite Lian et al. (2019)'s findings that low loan rates foster increased investment in risky assets, our study presents a contrasting outcome: reduced borrowing costs encourage higher cash reserve retention by the firm.

We permit the firm to determine the total committed credit lines, comprising both credit line drawdowns and unused credit lines. Despite the firm's considerable bargaining power in negotiating line commitments, the principle of maximizing wealth precludes the firm from retaining an infinitely extensive range of commitments.[1] This observation underscores that firms utilizing revolving credit facilities must bear the direct costs associated with on-balance-sheet debt (i.e., borrowing costs of credit line drawdowns) and off-balance-sheet factors (i.e., commitment fees for unused credit lines) as they direct external funds toward investments. In this manner, they must balance their role in generating wealth and the costs linked to selecting credit lines.

To underscore the significance of the wealth maximization policy, we construct an alternative model premised on asset maximization. If managers shift their focus from generating shareholders' equity to generating assets, the firm's profits will decline by 7%. This places the firm in a quandary, pitting overall asset expansion against the generation of shareholders' wealth in the context of investment decision-making.

As we investigate the purpose of credit line drawdowns as a funding investment, we investigate how credit line utilization correlates with a company's unique productivity, particularly under varying market conditions. In stable economic environments, firms with higher productivity (referred to as high-yield firms) possess greater borrowing capacity from revolving credit facilities than firms with lower productivity (referred to as low-yield firms). These high-yield entities can leverage the advantages of accessed funds' flexibility, whereas low-yield firms encounter significantly limited alternatives. However, when both categories of firms confront high-risk market scenarios, such as the COVID-induced recession, they exhibit analogous behavioural tendencies. As the overall risk escalates, these firms engage in what can be termed "panic borrowing," drawing from multiple credit lines extensively. Subsequently, as the market begins to recuperate, they curtail their credit line utilization as they scale back on line commitments.

The indirect cost of credit lines encompasses limitations stemming from the covenant restrictions imposed by banks. These restrictions, synonymous with covenant breaches,

[1] Our model suggests, for instance, that opting for either €0.2 billion or €0.6 billion in committed lines won't yield maximum profit, whereas €0.4 billion emerges as the optimal amount.

serve as crucial mechanisms through which banks oversee credit line agreements and curtail firms' withdrawal actions (refer to Sufi (2009), Acharya, Almeida, Ippolito & Perez-Orive (2014), Chodorow-Reich & Falato (2022)). By incorporating covenant breaches into the assessment of corporate default risk, an innovative discovery emerges: a firm's wealth exhibits an inverse correlation with its ability to access unused credit lines. This implies that heightened covenant stringency corresponds to elevated corporate profitability.

In the concluding phase of our analysis, we empirically assess the model's efficacy in explaining the utilization of revolving credit facilities. We procure firm-level credit line and balance sheet data from a consistent source, Bloomberg. Following the methodology of Hennessy & Whited (2007), we employ a structural estimation technique known as the simulated method of moments (SMM). Our estimation outcomes reveal that a 1% increase in risky assets corresponds to a 0.64% rise in production. To delve into shifts in firms' productivity amid the COVID-19 pandemic, we establish two distinct subsets representing periods before and during the pandemic. Notably, we identify a substantial 60.8% decrease in corporate productivity during the pandemic. By categorizing firms based on their exposure to the pandemic, we investigate the influence of the labour factor on corporate productivity during the lockdown induced by the pandemic.

Our research intersects multiple streams of literature. Initially, we draw from the growing body of work that employs theoretical models to elucidate corporate investment and financing strategies quantitatively. Some early foundational theoretical papers include Campbell (1978), Boot et al. (1987), Berkovitch & Greenbaum (1991), Duan & Yoon (1993), Holmström & Tirole (1998), Morgan (1994), and Thakor (2005). Our contribution to this field lies in our explicit consideration of liquidity management. In contrast, recent theoretical works such as Acharya, Almeida, Ippolito & Perez (2014*a*), Nikolov et al. (2019), Greenwald et al. (2020), and Cooperman et al. (2023) predominantly focus on credit line lenders, specifically banks. In this study, we shift the spotlight to explore credit line usage behaviours from borrowers' perspective, i.e., firms, providing additional insights into this area.

Moreover, this thesis maintains a close connection with the body of literature focusing on the interplay between credit lines and capital structure, as evidenced by studies such as Shockley (1995), DeMarzo & Sannikov (2006), DeMarzo & Fishman (2007), and Biais et al. (2007). However, we distinguish ourselves from these models by dynamically deriving credit line drawdowns and equity as optimal securities. In contrast, our model delves into capital structure optimization from a relatively static standpoint, encompassing only two periods, offering a convenient extension avenue. This approach allows us to investigate the impact of macroeconomic conditions (e.g., risk-free rate and shock term) and idiosyncratic productivity on the firm's profitability.

A robust nexus to the existing literature emerges in the relationship between credit lines and corporate default risk. Limited studies, including Mester et al. (2007), Jiménez et al. (2009), and Norden & Weber (2010), empirically showcase how the quality of borrowers influences debt contracts and financial intermediation. Our contribution lies in providing a theoretical framework that rationalizes this intricate process.

Furthermore, our contribution extends to public economics, particularly in discussions surrounding the labour ramifications of the COVID-19 pandemic. Studies like Dingel & Neiman (2020), Adams-Prassl et al. (2020), and Mongey et al. (2021) delve into the inequality of pandemic exposure across industries. This thesis builds upon these inquiries by exploring the link between inequality and firms' productivity. Additionally, a handful of works, exemplified by Campello et al. (2020), delve into the interrelation between the labour factor and credit line utilization. Our study aligns with and enriches this line of research.

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Chapter 2

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

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 report some new and interesting results. First, heterogeneity across countries and industrial exposure to the COVID-19 shock helps us to understand why some firms drew down credit lines in March 2020. Banks accommodated the demand for credit insurance during the same period. Our study exploits the implications of social distancing policies on corporate operations across Europe. The novel aspect of our study is that, differently from the previous literature, we focus on shocks unrelated to firms' fundamentals. 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, financial constraint
Classification codes: G21, G32, G33

2.1 Introduction

Over the past decade, credit lines have channelled a significant amount of credit from banks to European enterprises.[1] We estimate that European firms (the euro area) drew down over €87bn[2] in a short time to stay afloat. This 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). Acharya et al. (2020) show similar results for US firms.

There is extensive literature on firms' liquidity risk management using credit lines (e.g. Campello et al. (2011) and Acharya et al. (2012). More are cited below). Our paper focuses on an aspect that has not been largely investigated: firms' liquidity risk management when hit by an unpredictable shock (in our case, the COVID-19 shock), which is completely exogenous to firms' fundamentals and is idiosyncratic to some firms. In this respect, our paper is closely related to Brown et al. (2021). They study firms' short-term liquidity risk management when firms are affected by weather shocks. We generalise and extend that idea to the COVID-19 shock. Note that these two shocks are substantially different in the way they may impact aggregate risk. It is an important departure from Brown et al. (2021). For example, Acharya et al. (2013) show that shocks increasing aggregate risk can limit the amount of credit insurance available to firms. In order to obtain clear empirical answers to the issues cited above, we need to specify our econometric model correctly. In fact, we aim to establish that firms' cash flow variability results from the COVID-19 shock and not from changes in firms' long-term profitability (or firms' fundamentals). We explain below how we achieve this goal.

To summarise some of our results, we show that financially unconstrained (European) firms, at the peak of the COVID-19 shock, went into a "panic borrowing status" and drew down credit lines after experiencing a sharp drop in their expected cash flow. This result holds for the firm level, even when we extend our analysis to country and industry levels. The extension of our analysis to the country and industry level allows us to study if the heterogeneity of firms' exposure to the COVID-19 shock matters for liquidity risk management. We show clear and significant empirical evidence that heterogeneity amongst borrowers is important. Firms (in countries and industries) highly exposed to the COVID-19 shock drew down credit lines and accumulated cash. These new results complement the recent literature on firms' credit line drawdowns during the COVID-19 shock (Acharya et al. 2020) by introducing a new risk dimension: work

[1] This paper is an updated version of the working paper by Cerrato et al. (2023). We strengthen the discussions of data selection and shrink the ones of financial constraints to make the paper concentrate on how credit line drawdown decisions are related to short-term liquidity risk management.

[2] We also use Capital IQ as an alternative database. The Bloomberg database used in this paper accounts for 80% of credit line drawdowns in the Euro area within the same period.

(country) flexibility.

Our results also have important policy implications and help us to understand corporate liquidity management when shocks are unrelated to firms' fundamentals. For example, Acharya et al. (2013) show that shocks increasing aggregate risk can affect the supply of credit insurance. For the COVID-19 shock, we show that banks supplied the requested credit insurance during that period. Banks helped firms more exposed to the COVID-19 shock to manage their (short-term) liquidity risk. Our empirical evidence and the extensive literature covering the 2008 financial crisis suggest that the type of shock matters in understanding why firms draw down their credit lines and banks' decisions to supply credit insurance.

As we explained above, we mitigate the effect of endogeneity in different ways. In the first part of the paper, by controlling for observable factors that could be jointly correlated with firms' decisions to draw down credit lines (Acharya et al. 2020, Bosshardt & Kakhbod 2020). Thereafter, we also employ a battery of quasi-natural experiments as well as instruments.

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, they are contingent liquidity lines that can be seen 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).

Figure (2.1) 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 was 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 (2.1) 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. There is indeed a significant heterogeneity in which firms drew down credit lines.

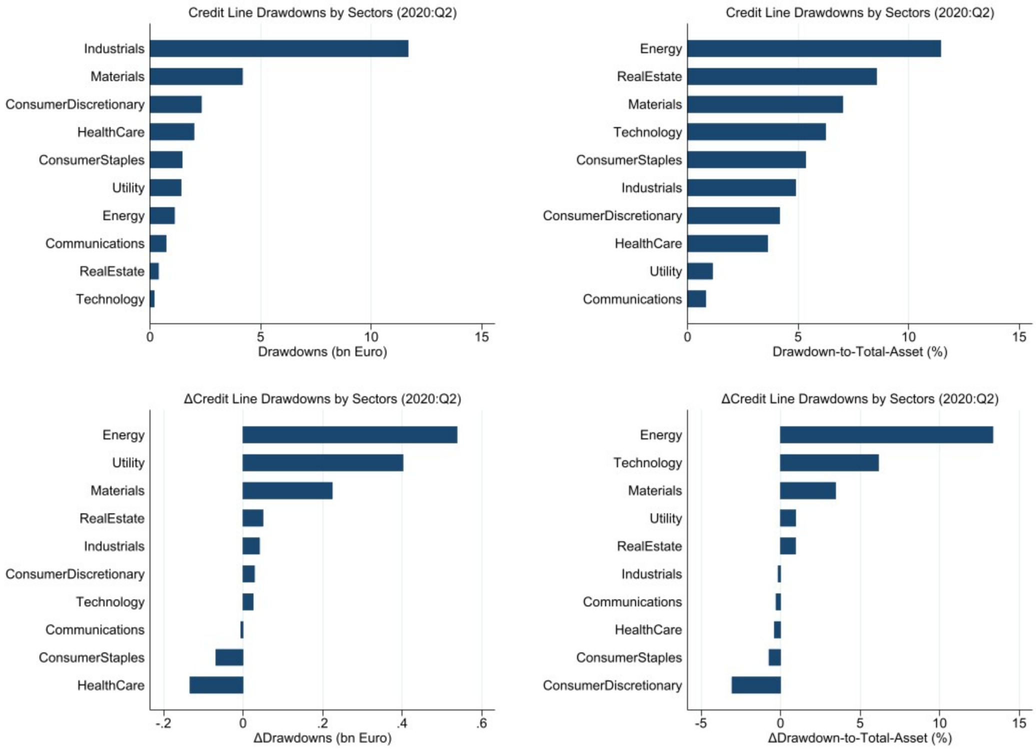

Figure 2.1. Industrial Distribution of Credit Lines.

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 significantly 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.

There is extensive literature on credit insurance and firms' liquidity risk management. This literature is largely based on theoretical models such as Shockley & Thakor (1997) and Holmström & Tirole (1998), which suggest that the difference between credit lines financing and debt is that credit lines are credit insurance, allowing firms to access credit at the time they need the most. These models mainly consider endogenous shocks (that is, due to bad management decisions).

One of the first empirical studies is Sufi (2009), which studied the substitution effect between internal (cash holdings) and external (credit lines) before the 2008 financial crisis, that is, in a period when credit was abundant. Sufi shows that firms using credit lines are generally profitable, while not profitable firms find it difficult to access credit through credit lines exactly when they need it the most. That paper assumes that endogenous shocks (i.e. bad management decisions) drive the demand for credit insurance. Acharya, Almeida, Ippolito & Perez (2014*b*) complement Sufi (2009) and explain why banks revoke credit lines to unprofitable firms. They show that banks use covenants to monitor firms' liquidity management. It follows that firms using credit lines have lower liquidity risk than the ones using cash holdings. We complement these results in several ways. First, we consider a complete exogenous shock. We employ an empirical identification approach to restrict our analysis to short-term liquidity risk management. Finally, we provide robust evidence that banks and firms cooperate during the COVID-19 shock.

Campello et al. (2011), using data for the 2008 financial crisis and US firms, show a substitution effect between cash holding and credit lines when firms face a severe credit shortage. They show that firms with more internal funds borrow less from credit lines, even if these credit lines are cheaper for them. Ivashina & Scharfstein (2010) find that borrowers used their credit lines during the 2008 financial crisis for precautionary reasons. We extend and complement these studies by considering the COVID-19 shock and show that less financially constrained firms dashed for cash during the COVID-19 period. We also show that the panic borrowing observed for US firms (Campello et al. 2011, Ivashina & Scharfstein 2010) during the 2008 financial crisis does not extend to European firms.

More recently, a strand of the literature about firms' liquidity risk management during COVID-19 has emerged. While Halling et al. (2020) studied different financing methods (mainly bonds and equity) during the COVID-19 pandemic in the US, Schivardi et al. (2020) studied zombie lending during that period. Calabrese et al. (2022) study the role of UK government support to Medium Size Enterprises (SMEs) during the COVID-19 shock. Although the cited literature makes important contributions to our understanding of how firms exploited the COVID-19 shock to open up new markets or the role of governments in supporting firms to stay afloat during the COVID-19 period, they are only mildly related to our paper.

One of the papers that are more related to ours is Acharya et al. (2020). They show that US firms borrowed a significant amount of money from their credit lines in March 2020. They also show that firms using credit lines were, at least at the beginning of the period, less constrained firms. We complement and extend these results in several different ways. The COVID-19 shock led to a policy response across Europe, which needed to be more 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), showing that country flexibility is essential. Firms in countries where COVID-19 infection rates were higher and policy measures stricter went into a "panic borrowing" and drew down their credit lines.

We consider work flexibility as in Campello et al. (2020) to exploit heterogeneity across countries and industries fully. They show for the US that work flexibility is necessary to understand job hiring in the US during the COVID-19 period. Work flexibility is also crucial to understanding firms' behaviour, such as "panic borrowing". Besides, we show that work flexibility is unique to the COVID-19 crisis and does not extend to the 2008 financial crisis or the 2012 European crisis. In sum, our results suggest that the type of shock and heterogeneity across countries and industries are important to understand: i. the panic borrowing observed during COVID-19; ii. the way banks cooperate with some firms (in some countries) and not with others. These are important results that we add to what was reported in Acharya et al. (2020) for the US. Of course, we admit that our results cover only part of the story of what happened in March 2020. For example, we do not consider government intervention, cultural differences across countries and more. However, our empirical evidence is still important as it opens up new (theoretical and empirical) research questions for the future. We leave it on our agenda for the near future.

It is also worth citing an additional strand of the literature that emerged in the early part of the COVID-19 shock. This literature studies the relationship between shutdowns following COVID-19, employment opportunities and new markets. For example, Kogan et al. (2020) finds that industries with fewer opportunities to work from home performed worse as measured by declines in employment, expected revenue growth and stock market performance. On the other hand, Barrero et al. (2020) and Hassan et al. (2020) show that some firms exploited the shutdown opportunity to enhance investments in new markets. We contribute to this strand of the literature by focusing on firms' liquidity management in March 2020 and the interplay between firms and banks for the demand and supply of credit insurance.

Finally, our paper also speaks to the growing and recent literature on the effect of natural events and COVID-19 on firms' liquidity risk management (Koetter et al. 2020, Verbeke 2020, Brown et al. 2021, Calabrese et al. 2022, Sun et al. 2022). We complement these studies by shedding further light on some of their results and the implications for banks. For example, Sun et al. (2022) find strong evidence that cash holdings are negatively associated with firm financial hedging activities. Our undrawn credit line variable, used as a control in the empirical analysis, can be seen as a measure of hedging against a liquidity shock. It is always positive and statistically significant in our analysis, implying that firms are hedging liquidity risk using credit lines rather than cash holdings.

2.2 Data

We source all information on corporate credit lines from Bloomberg, including the total amount of committed credit lines, the total available credit lines, and credit line usage. Total credit line refers to the total amount of committed lines of credit that firms can access. Typically, it contains the drawn and the undrawn credit lines. Since Bloomberg has no direct information on credit line drawdowns, we use the available credit line as a proxy for the undrawn credit line. We calculate the drawdowns as the total committed line minus the available credit line.[3] For credit line usage, we divide credit line drawdowns by total committed credit lines.

We supplement credit line data by including firms' financial variables from Bloomberg, with all financial data measured in euros. We obtain these data from all the firms with available information between 2018:Q4 and 2020:Q3. For firm selection, 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. The industry classification used in this paper is based on the Bloomberg Industry Classification System (BICS).[4] However, we must still match this novel industry classification with the North American Industry Classification System (NAICS). Then, we can merge our data with O*Net for investigating the COVID-19 industrial exposure, based on literature (e.g. Dingel & Neiman (2020), Adams-Prassl et al. (2020), and Campello et al. (2020))[5]. At last, there were 324 non-financial firms in total from 2018:Q4 to 2020:Q3[6]. These firms come from 15 different countries. The countries with the largest number of firms are Finland (33.74%), Germany (26.75%), Italy (7.16%), Spain (6.47%), and France (6.13%). Although Finnish firms might be keen to access credit lines, the amount of borrowing is not significant[7]. Regarding industrial distribution, the industries with the largest number of firms are

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

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

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

[6]Note that ours is an unbalanced data-set running from 2018Q4 to 2020Q3.

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

Industrials (26.14%), Consumer Discretionary (14.32%), Materials (13.98%), Technology (10.61%), and Communications (8.89%). We have 10 BICS sectors in total.

We also collect (country-level) quarterly data on the COVID-19 confirmed cases per million from the European Centre for Disease Prevention and Control (ECDC). Meanwhile, we obtain data on social distancing strictness across European countries from Our World in Data, following Ritchie et al. (2020)'s research in the Oxford Stringency Index.

Following the literature (e.g. Campello et al. (2011), Acharya et al. (2012), and Acharya et al. (2020)), we use firms' characteristics that may affect utilization of revolving credit facilities during the COVID-19 shock: cash holdings, leverage, firm size (measured by the logarithm of total assets), tangible assets, undrawn credit lines, and price-to-book ratio. Cash holding is an important driver of corporate credit line usage. Firms with internal liquidity have better repayment abilities, enabling them to access external funds like revolving credit facilities.

Capital Expenditure and leverage may have a remarkable impact on credit lines. Early theoretical papers highlighted their roles in understanding credit line drawdowns (e.g. Martin & Santomero (1997) and Holmström & Tirole (1998)). Firm size and tangible assets are also important in corporate credit lines (see amongst the others Chodorow-Reich et al. (2022) and Nikolov et al. (2019)). Finally, undrawn credit lines provide potential drawn amounts for the next period. The price-to-book ratio (P/B) is a valuation tool to assess whether a firm's stock price is overvalued or undervalued relative to its book value per share. It reflects the firm's financial performance in the secondary market.

In section 2.3, we study the firm's financial constraints and credit line drawdowns. We employ a risky-investment-to-debt ratio (RID) based on corporate capital structure. It is a proxy for credit risk, based on Allen et al. (2015)'s financial intermediation model of banks and builds up this ratio to measure a firm's solvency constraints (see description in section 2C). As a proxy for liquidity distress, we use Bosshardt & Kakhbod (2020)'s method (see description in section 2C). Both indicators are derived from corporate financial information that we collect from the Bloomberg database.

Finally, following the definition in literature (Sufi 2009, Acharya & Steffen 2020*b*, Greenwald et al. 2021, Brown et al. 2021), we use the earnings before interest, taxes, depreciation, and amortization (EBITDA) to measure a firm's cash flow.[8]

[8]Literature sometimes denotes EBITDA as profitability or ROA (return on assets), but these concepts are equivalent to cash flow.

Table (2.1) shows the summary statistics. All variables are normalized by total assets. The average (median) credit line drawdowns are 4.5% (0%)[9]. The average (median) credit line usage is 20.7% (0%). Revolving credit lines are facilities commonly used by banks to supply cash to firms. The average (median) firm has cash flow around 2.5% (2.5%), given solvency constraint and liquidity distress around 0.309 (0.380) and –0.025 (-0.019), respectively. As for financial characteristics, the average (median) firm has a cash holding of 8.9% (7%), capital expenditure of 1.1% (1.5%), leverage ratio of 30.2% (28.3%), the logarithm of total assets of 21.52 % (21.64%), the tangible asset of 75.3% (80.9%), undrawn credit line of 10.6% (8.4%), and the logarithm of price-to-book ratio of 0.53 (0.52). Alternatively, we include free cash flow to study the revenue shortfall, with an average (median) value of 1.6% (1.4%).

Most firms are highly exposed to the pandemic, with an average (median) 65.8% (78%) jobs that could not be done at home in 2020. Compared with low-exposed firms, those with high exposure account for 78%. In terms of country-level data, the average number of COVID-19 confirmed cases was around 1654 ($= e^{7.411}$) per million. Appendix 2B Table 2B1 documents the cases across countries in our sample. Around 63.7% of firms were highly exposed within countries with relatively high infection rates. The average (median) firms located in countries with moderate strictness of lockdown policy, around 50.9 ($= e^{3.93}$).[10]

Figure (2.2) shows the weighted credit line drawdowns and credit line drawdown size for all Euro-area firms in the sample. In the left-hand-side panel, we scale drawdowns by the number of firms each quarter. European firms drew down credit lines at the start of the pandemic.

In Figure (2.3A), we note a significant increase in cash holdings during the same period. The increase in cash holdings could be associated with investments. This Figure also shows the trend in liquidity accumulation before and after the pandemic period. Specifically, average cash holdings, including cash and cash-equivalent components, scaled by total assets, increased sharply during the pandemic. The sharp increase in cash holdings is consistent with Anderson & Carverhill (2012) and Bolton et al. (2011) and suggests an increase in liquid assets, 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 (2.3B), we use capital expenditure as a proxy for investment. There is

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

[10]According to Ritchie et al. (2020), the index of 100 indicates the strictest lockdown policy, while the score 0 means the absence of social distancing.

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 the Online Appendix, we confirm 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.

Table 2.1. **Summary Statistics.**

This table reports the summary statistics for the full sample. Appendix (2A) provides the definition of all variables.

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

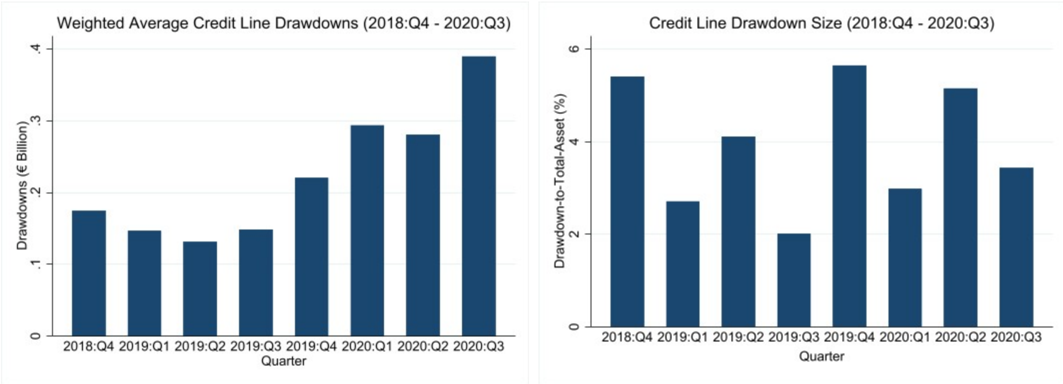

Figure 2.2. Average Credit Line Drawdowns

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

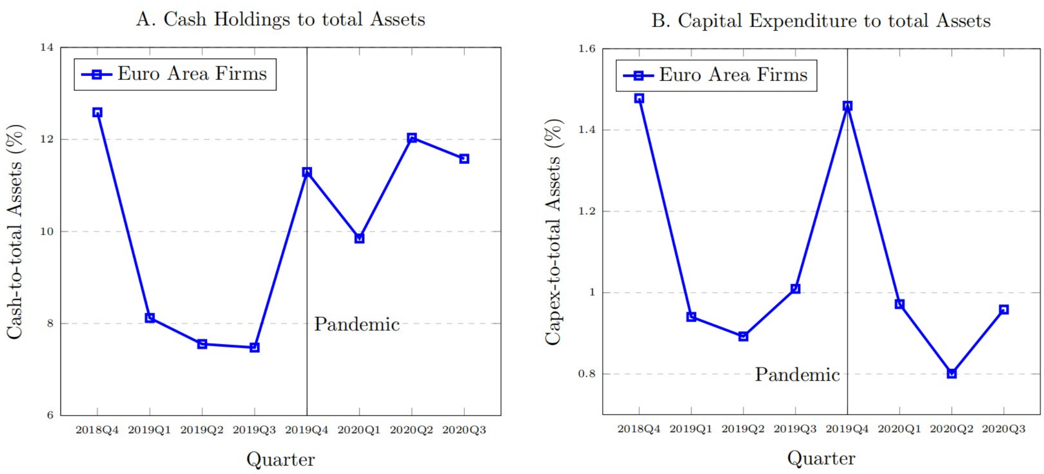

Figure 2.3. Cash Holdings and Capital Expenditure.

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

2.3 Financial Constraints

In this section, we study whether firms in our dataset are financially constrained. It will help us to establish in the next sections that corporate credit line drawdowns are not correlated with firms' fundamentals. Sufi (2009) shows that less financially constrained firms generally rely on credit lines while financially constrained firms use cash to manage liquidity shocks. However, Sufi's study investigated the period before the 2008 financial crisis when credit was abundant. Campello et al. (2011) study firms' real side (investment) decisions and credit lines during the financial crisis period and show that firms substitute cash holding with credit lines in the presence of liquidity shocks. Acharya & Steffen (2020*b*) show that US firms raise cash to offset changes in credit risk following the COVID-19 shock.

We investigate if solvency constraint correlates with a firm's decisions on credit line drawdown. We extend the risky-investment-to-debt ratio (RID) measured in Allen et al. (2015) and use lagged value[11]. Detailed descriptions of the RID ratio and empirical results are presented in Appendix 2C. In Table (2.2) Panel A, we summarize our results of solvency risk after sorting firms (in 2020:Q2) into three groups according to the RID: Low (25%), Medium (50%) and High Risk (25%).

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. Lower-risk firms (in terms of solvency) drew down their credit lines 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.[12]

We now investigate liquidity constraints and measure them using *Distress* (Bosshardt & Kakhbod 2020). Higher (lower) Distress implies a tighter (looser) liquidity-based financial constraint reflecting capacity to meet current liabilities. Detailed information on these liquidity constraints and additional empirical results are provided in Appendix 2C.

In Table (2.2) Panel B, we also report our results of liquidity distress after dividing firms (in 2020:Q2) into three groups according to *Distress*: Low (25%), Medium (50%) and High Distress (25%). The results again confirm that firms drawing down credit lines are not liquidity constraints. Overall, firms drawing from credit lines seem to be financially unconstrained firms. This result is in line with Sufi (2009) but contrasts with Campello et al. (2011) although they investigate a different shock (2008 financial crisis shock) and a different market (US).

[11]Although RID is a proxy for solvency constraint, it consists of balance sheet items. We follow Jiménez et al. (2009) and use lagged value to better capture the firms' operation and avoid possible endogenous issues.

[12]We have also included Cash Holdings in Table (2C2) and the coefficients are significant but positive. Therefore, we exclude that a substitution effect between internal and external funding occurred in 2020:Q2.

Table 2.2. **Financial Constraints and Drawdowns**

This table shows the relationship between two types of financial constraints, solvency risk and liquidity distress, and credit line drawdowns. 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 credit lines usage. Panel A shows how the solvency risk (RID) correlated with the drawdowns, given the interactions between the RID ratio and time dummies (*2020:Q1-Q3*), respectively. Panel B shows how the liquidity distress (Distress) correlated with the drawdowns, given the interactions between the Distress and time dummies (*2020:Q1-Q3*), respectively. Columns (2) - (4) and columns (6) - (8) show three subsamples: *Low-, Medium-*, and *High-Risk (Distress) Firms.* Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Note that the different number of observations in Panels A and B is due to using lagged RID. Distress is a contemporaneous variable which, in principle, causes no reduction in sample size.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Firms	Low Risk	Medium Risk	High Risk	All Firms	Low Risk	Medium Risk	High Risk
Panel A: Solvency 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)
$\text{RID}_{t-1}\times$2020:Q2	-0.061*	-0.173***	0.046	0.092	-0.199*	-0.556*	0.283	0.284
	(0.032)	(0.054)	(0.174)	(0.240)	(0.109)	(0.296)	(0.478)	(0.818)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	388	83	199	105	381	79	199	102
Adjusted R^2	0.066	0.127	0.019	0.189	0.063	0.017	0.085	0.241
Panel B: Liquidity Distress								
Distress_t	0.240***	0.368**	-0.038	0.830***	0.417***	1.347***	-0.916*	0.990***
	(0.047)	(0.156)	(0.151)	(0.109)	(0.133)	(0.428)	(0.470)	(0.307)
$\text{Distress}_t\times$2020:Q2	-0.188***	-0.360**	-0.133	0.119	-0.283*	-1.302***	0.189	0.524
	(0.052)	(0.158)	(0.403)	(0.254)	(0.148)	(0.434)	(1.252)	(0.713)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	804	238	416	148	788	231	410	145
Adjusted R^2	0.047	0.076	0.021	0.383	0.024	0.085	0.052	0.186

2.4 Corporate Characteristics

2.4.1 Shortfall in Revenue and Credit Line Drawdowns

In this section, we focus on corporate characteristics and credit line drawdowns. The previous section shows that the sampling firms drawing down credit lines in March 2020 had good liquidity and solvency positions. While it is unlikely that the COVID-19 shock has significantly impacted their long-term investment plans, it may have affected their short-term liquidity needs. Thus, in the rest of this paper following Brown et al. (2021), we study whether drawdown decisions are related to short-term liquidity risk management. We conjecture that these firms experienced a significant shortfall in expected revenue (or cash flow) and drew down their credit lines to manage cash flow risk. 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.

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. Acharya & Steffen (2020*b*) study liquidity risk management for the US firms during the COVID-19 shock, but they assume that the shock affected all the firms (in different sectors) similarly. We complement and extend that paper by studying heterogeneity across firms (and sectors) and show that it is important.

We use cash flow as measured by the EBITDA, net income with interests, taxes, depreciation, and amortization, and include time and industry fixed effects. We expect that firms with lower expected cash flows will be hit by the COVID-19 shock and draw down credit lines.

$$\begin{aligned} \text{Drawdown}_{i,t} &= \beta_0 + \beta_1 \text{EBITDA}_{i,t} + \beta_2 \text{EBITDA}_{i,t} \times \text{2020:Q2} + \\ &\quad \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.1}$$

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.[13] We consider firms with at least one observation before and after 2020:Q2.[14]

[13] Refer to section 3.2 for further details in controls we use in this paper.

[14] Results not included in this paper show that the results we report in this section are robust after

We show the results in Table (2.3) and include three dummies, one for each quarter.[15] 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). 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. Credit line usage results are summarized in columns (4) to (6). We note marginally significant cash holdings in very few cases. These results support our conjecture that Europe's "panic borrowing" in 2020:Q2 was significant and led firms with lower expected cash flow to draw down their credit lines (Acharya et al. 2020).

In Table (2.4), we divide 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, 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 line drawdowns in firms' decisions. We shall consider the endogeneity issue in the next section.

2.4.2 Robustness Checks: A Discontinuity Analysis

In this section, we provide further empirical evidence that the COVID-19 shock affected firms' expected cash flows and, as a consequence, they drew down credit lines.

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

$$\text{Drawdown}_{i,t} = \beta_0 + \beta_1 D_{i,t}(\lambda) + \beta_2 D_{i,t}(\lambda) \times 2020\text{:Q2} + \gamma X_{i,t} + \epsilon_{i,t} \quad (2.2)$$

where λ denotes the choice of neighbourhood bandwidth such that D_i, t is equal to a firm performance outcome within $[0, \lambda)$ bandwidth and zero otherwise.[16] The notations follow the definition in equation (2.1) 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

accounting for survival bias, particularly when a certain fraction of firms face bankruptcies. These results are available upon request.

[15] In Online Appendix Table A1, we report the lagged specification, which still supports the results.

[16] 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.

Table 2.3. **Credit Line Drawdowns and EBITDA**

The table shows firms' reliance on credit lines (columns 1-3) and credit line usage (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 the 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. All variables are defined in Appendix 2A1. 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	-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 2.4. **Credit Line 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 variables in columns (1) to (4) are credit line drawdowns scaled by total assets. The dependent variables in columns (5) to (8) are the usage of credit lines. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between the distress and time dummies (*2020:Q2*). Apart from the whole sample (columns (1) and (5)), the regression is also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. All variables are defined in Appendix 2A1. 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)
EBITDA_t	-1.357***	-2.760**	3.163	0.427	-3.327**	-7.400**	18.228*	-0.685
$\times$2020:Q2	(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

provide a quasi-randomisation experiment as realisations just above or below the zero thresholds drive firms' decisions to draw down credit lines. We expect that firms with performance just above the zero thresholds tend to behave differently from those with realisations just below the threshold.

The results are presented in Table (2.5), 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 2020:Q2 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. These results confirm that during the pandemic shock, firms exhibited a shift in their drawdown decisions to manage short-term liquidity risk following a shortfall in revenue. Note that these results contrast with Sufi (2009) and Campello et al. (2011), who find that more profitable firms draw down credit lines. The empirical evidence supporting the "panic borrowing" is robust and seems driven by a firm revenue shortfall.[17]

[17] Appendix 2E reports an alternative design of regression discontinuity where we show that the empirical evidence in Table (2.5) is robust.

Table 2.5. **Regression Discontinuity Design and Credit Line Drawdowns.**

This table shows credit line drawdowns on revenue within various groups based on cash flow. The dependent variable is *Drawdown Size*, credit line drawdowns scaled by total assets across all columns. 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 of the 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. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

2.5 Country-level COVID Impact

In sections 2.3 & 2.4, we show that financially unconstrained firms hit by the COVID-19 shock experienced a sharp fall in cash flow and drew down credit lines. In this section, we extend these results to the country level. We conjecture that firms in countries more affected by the COVID-19 shock used their credit lines more. We believe that studying this heterogeneity is important to fully understand why the demand for credit increased during the COVID-19 shock (see previous sections). We also study if banks accommodated the demand for credit and provide possible explanations for that. In doing so, we add to Acharya et al. (2020) as we study heterogeneity across countries and if this is important to understand banks' supply of insurance credit.

We first construct a novel empirical measure of social distancing using COVID-19 confirmed cases and the Oxford Stringency Index (see Online Appendix for the distribution of confirmed cases across countries and details about how we construct COVID-19 measures).

2.5.1 Lockdown Policies, Credit Line Drawdowns and Cash Accumulation

We consider the country's infection data (see Appendix 2B for further details) and specific social distancing policy (less or more stringent). We extend the approach in Campello et al. (2020), who study job hiring in the US and work flexibility. The idea of doing this is to directly use country-level information on COVID-19 cases to study if the "panic borrowing" is a consequence of high COVID-19 cases and stringent policy measures. 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.

Infection rates, mobility policy and credit line drawdowns

We use Equation (2.3) below to study the relationship between infection rates (mobility policy) and firms' credit line drawdowns.

$$\begin{aligned} Drawdown_{i,t} &= \alpha + \beta_1 COVID\ Impact_{i,t} + \beta_2(COVID\ Impact_{i,t} \times 2020{:}Q2) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.3}$$

where $Drawdown_{i,t}$ denotes: 1) credit line drawdowns divided by total assets, and 2) credit line usage. $COVID\ Impact_{i,t}$ is once 1). $High\ COVID\ Exposure_{i,t}$, a dummy equal to 1 each quarter the country is in the top 50% of the number of confirmed COVID cases per million and 0 elsewhere (Campello et al. 2020); 2) We also use $\log(Stringency)$, the logarithm of the Stringency Index which records the strictness of "lockdown style" policies. Higher Stringency Index restricts people's access to some jobs (Ritchie et al. 2020). *2020:Q2* is a time dummy that 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 (2.3) are documented in Table (2.6).

Table (2.6) shows that, generally, firms reduced access to credit lines during the sample period but increased reliance on credit lines in 2020:Q2. Our results using the Stringency Index are even more supportive and show that more stringent social distancing rules lead to higher drawdowns. At the peak of the COVID-19 shock, European firms were facing a shortfall in revenue due to the unexpected lockdowns across Europe, which led to a "panic borrowing" status. In a nutshell, firms dashed for cash to manage short-term liquidity risk. Our results also 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 and, subsequently, a government policy (lockdown), which triggers cash accumulation.

Social distancing policies across European countries

This section only focuses on the four largest economies in the Euro Area. We complement the results in Table (2.6). Figure (2.4) shows 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.

We construct a specification to investigate the relationship between credit line draw-

Table 2.6. **The Impact of COVID-19 on Credit Line Drawdowns During the COVID-19 Shock.**

This table presents the regression results of Equation (2.3). The dependent variables across all columns are $Drawdown_{i,t}$, 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 that 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. All variables are defined in Appendix 2A1. We show robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High COVID	-0.066***	-0.078***			-0.225***	-0.294***		
Exposure	(0.013)	(0.015)			(0.043)	(0.049)		
High COVID		0.022				0.130***		
Exposure×2020:Q2		(0.015)				(0.049)		
log(Stringency)			0.037**	0.045**			0.161***	0.183***
			(0.019)	(0.019)			(0.060)	(0.061)
log(Stringency)				0.007**				0.020*
×2020:Q2				(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

downs and the strictness of lockdown policies across countries as follows:

$$\begin{aligned} Drawdown_{i,t} &= \alpha + \beta_1 log(Stringency)_{i,t} + \beta_2 (log(Stringency)_{i,t} \times Country_i) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.4}$$

where $Drawdown_{i,t}$ has same definition as explained earlier. $\log(Stringency)_{i,t}$ 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 the same definitions as previous specifications. Table (2.7) reports the regression results of Equation (2.4).

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 line drawdowns differs across countries. For example, it is larger for Italy than Spain. Although our results are inconclusive, and we acknowledge the need for further investigation in the future, they suggest that the different lockdown measures across European countries have somehow impacted 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.[18] These results have important policy implications given that social distancing policies can generate negative externalities for firms and unexpectedly fly to liquidity.[19]

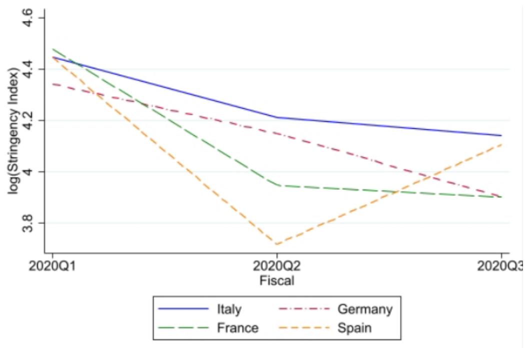

Figure 2.4. Country Distribution of Lockdown Stringency.

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.

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

[19]Credit line drawdowns also have serious implications for banks' liquidity management. As 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.

Table 2.7. **The Impact of COVID-19 on Credit Line Drawdowns (Countries).**

This table shows the regression results of Eq. (2.4). The dependent variables across all columns are $Drawdown_{i,t}$, 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. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. Industry fixed effect is included. All variables are defined in Appendix 2A1. We report robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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)	0.018***				0.045**			
×Italy	(0.006)				(0.020)			
log(Stringency)		0.000				0.030**		
×Germany		(0.004)				(0.013)		
log(Stringency)			0.014**				0.041**	
×France			(0.006)				(0.019)	
log(Stringency)				0.012**				0.014
×Spain				(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

2.5.2 Robustness Checks: Empirical Identification

In this section, we provide some robustness that shows that differences in the spread of the virus across countries are important. We also provide additional empirical evidence that the COVID-19 shock has driven liquidity management decisions through its effect on expected revenue. This is important as we are interested in disentangling the causal effect of COVID-19 shock on short-term liquidity risk management. To do this, we use the same econometric setting as in Brown et al. (2021). The empirical strategy allows one to study the causal effect of a change in cash flow on credit line drawdowns. We use a 2SLS procedure:

$$EBITDA_{i,t} = \alpha + \beta_1 log(Cases)_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{2.5}$$

$$Drawdown_{i,t} = \alpha + \beta_1 \widehat{EBITDA}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{2.6}$$

The first stage is given by equation (2.5), where *EBITDA* is the cash flow defined as in previous sections. *log(Cases)* is the natural logarithm of the number of confirmed cases per million across European countries. In the second stage, equation (2.6), we regress drawdowns on predicted values from the first stage and a set of controls as in the first stage. The controls in the two stages are the same as in the previous sections. The definitions of all variables can be found in Appendix (2A1). 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. This allows us to study firms' liquidity risk management when shocks are uncorrelated with firms' (long-term) investment decisions.

Figure (2.5) shows the results from the first stage regression and confidence interval in each quarter between 2020:Q1 and 2020:Q3. Given the number of COVID-19 cases, the estimated change in cash flow decreased between 2020:Q1 and 2020:Q2 but increased thereafter. Firms responded to this shock by drawing their credit lines during that quarter. Panel A of Table (2.8) 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 2020:Q1-2020:Q3. They will help us understand if the panic borrowing is mainly concentrated in 2020:Q2 or extends to 2020:Q3. The estimated beta is highly significant in 2020:Q2 and significant in 2020:Q1 but becomes insignificant in 2020:Q3. Also, the estimated size of the coefficient is much larger in 2020:Q2, 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.

Did banks cooperate with firms to supply credit insurance? The evidence over the 2008 financial suggest that banks reduced the supply of credit. However, evidence for other shocks, such as weather shock as in Brown et al. (2021), suggests that banks cooperated with firms instead. We study this for a new shock: the COVID-19 shock. In Panel B of Table (2.8), 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' demand for insurance credit during the COVID-19 shock, providing them with the necessary liquidity.[20]

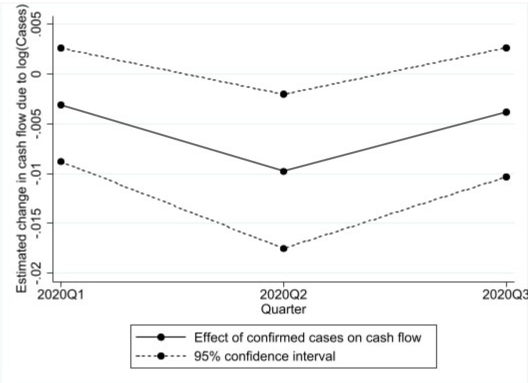

Figure 2.5. Cash Flow and COVID Confirmed Cases.

This figure shows the relationship between *log(Cases)* and firms' cash flow. The figure is estimated from three regressions of Equation (2.5), 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 interval on the estimation.

2.6 Industry-level COVID Impact

Section 2.4 shows that firms with good liquidity and solvency positions during the COVID-19 shock drew down credit lines. In section 2.5, we extend our results to a country level, showing that heterogeneity across countries in infection rates is important to understand why firms in certain countries used credit lines more than others to manage short-term liquidity risk. Interestingly, we report evidence that banks in countries more affected by the COVID-19 shock cooperated with firms. In this section, we take one step forward and extend these results to an industry level. Based on recent literature (Campello et al. 2020, Brown et al. 2021), we conjecture that firms more exposed to the COVID-19 shock drew down credit lines.

[20] 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.

Table 2.8. **Two-Stage Least Square (2SLS) Identification Strategy.**

This table reports both the OLS and 2SLS regression results of Equation (2.6) in different quarters. In panel A, the dependent variables are credit line drawdowns scaled by total assets across all columns. The independent variables are the EBITDA scaled by total assets. Columns (1), (3), and (5) are based on OLS regression within the first three quarters of 2020. Columns (2), (4), and (6) use log($Cases$) as an instrumental variable. Panel B uses total committed credit lines as dependent variables. Controls contain unused credit lines, the logarithm of the price-to-book ratio, tangible assets, and the leverage ratio. Fixed effects are included as indicated. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Panel A					
	Drawdown Size					
	2020:Q1		2020:Q2		2020:Q3	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	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)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	OLS	2SLS	OLS	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

2.6.1 Industrial Exposure to COVID-19 and Credit Line Drawdowns

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 important 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 firms' work and country flexibility following the COVID-19 shock, credit line 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 labourers 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,[21] and the definition of level-2 sub-sector remains generic. We develop a detailed matching across the two systems by exploiting the classification information

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

provided by each benchmark at level-3 industry groups and level-4 industries. Table (2.9) shows the industrial exposure to COVID-19 within two industrial levels. In Figure (2.6), we show firms' access to their credit lines between 2020:Q1 and 2020:Q2. Energy, Technology, Real Estate, and Materials were the ones that withdrew their credit lines during the pandemic shock.

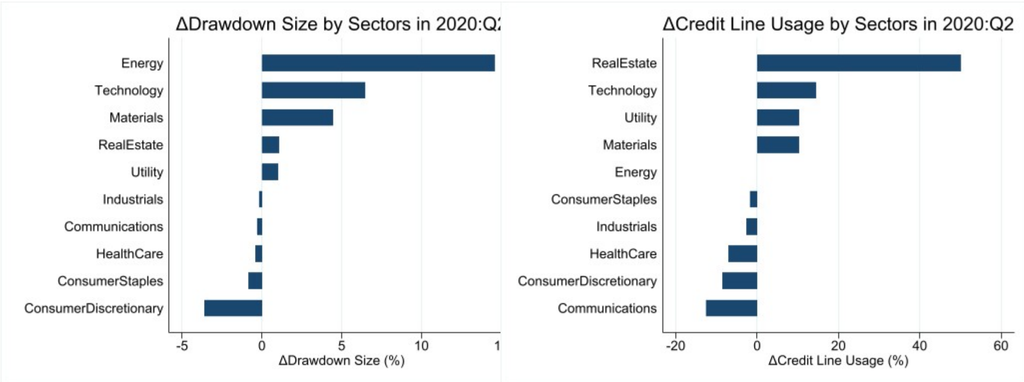

Figure 2.6. Industrial Distribution of Changes in Drawdowns.

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 firms' total assets.

2.6.2 Work Flexibility and Credit Line Drawdowns

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 start estimating the effect of social distancing on firms' credit line drawdowns, investment and cash holdings using a basic regression. We construct an industry fixed effect panel regression model using the following specification:

$$Y_i \quad = \quad \alpha + \beta_1(\textit{Industry Groups}_i \times \textit{2020:Q2}) + \gamma X_i + \epsilon_i \qquad (2.7)$$

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

Table 2.9. **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.

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	Elec. & Gas Mkting & 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		

capital expenditure scaled by total assets; and 3) Cash holdings, equal to cash scaled by total 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 (2.10) shows the results. During the pandemic shock, only firms less exposed to the pandemic shock reduced credit lines (Panel A). The remaining firms used more of their credit lines than they usually did. All the firms reduced investments. In Panel B, we can see that the coefficients of the interactions are negative, and only the one for the group *Mild*×*2020:Q2* is significant. If we consider cash holdings, both *Unexposed* and *Mild* increase the size of cash. The coefficient of the interaction *Exposed*×*2020:Q2* is negative but insignificant. Evidence shows that European firms used their credit lines for precautionary reasons and not for investment.

Panel A in Table (2.10) 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 (2.7) 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 line drawdowns and liquidity management as a new mechanism of firms' financial constraints.

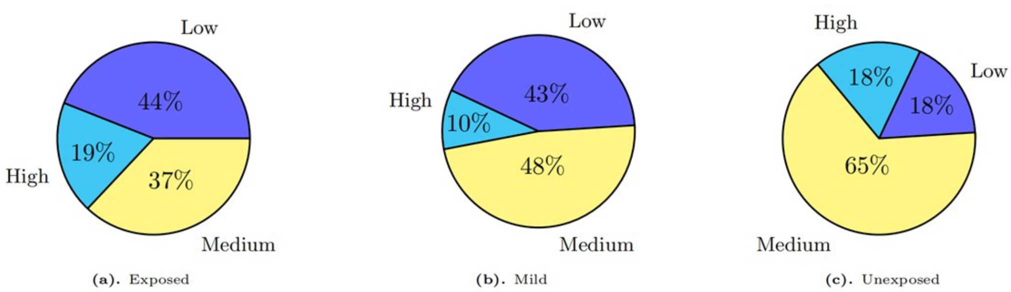

Figure 2.7. EBITDA by Exposure Levels.

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.

Table 2.10. **Regression Result: Industrial Exposure to COVID-19 (Euro Area)**

The dependent variables are credit line usage in Panel A, capital expenditure scaled by total assets in Panel B, and cash holdings scaled by total assets in Panel C. The independent variables contain three dummies: *Exposed*, *Unexposed*, and *Mild*. *Exposed* is the sector with a score higher than 0.75. *Unexposed* stands for the sector with a score lower than 0.3. *Mild* is the sector with a score between 0.3 and 0.75. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

2.6.3 Robustness Check: Empirical Identification

The previous results suggest that work flexibility (social distancing policy) is important to understand firms' drawdowns. However, we need to understand how the shock affects the firm and its decisions to draw down credit lines. In this section, we study this transmission channel. We employ an econometric setting similar to the one used in the previous section (2SLS). Following Campello et al. (2020) studying US employment during the COVID-19 shock, we conjecture that the inelastic nature of labour (less work flexibility) following the lockdown led to a sharp fall in expected revenue, especially in industries more exposed to the pandemic shock. We introduce an indicator function:

$$I(Exposure) = \begin{cases} 1 & \text{if } Exposure \geq 0.75 \\ 0 & \text{if } Exposure \leq 0.3 \end{cases}. \tag{2.8}$$

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:

$$EBITDA_{i,t} = \delta_0 + \delta_1.I(Exposure) + \eta_{i,t} \tag{2.9}$$

$$\begin{aligned} Drawdown_{i,t} = {} & \beta_0 + \beta_1 \widehat{EBITDA}_{i,t} + \beta_2 \widehat{EBITDA}_{i,t} \times \textit{2020:Q2} \\ & + \gamma X_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{2.10}$$

The first-stage regression in equation (2.9) 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 (2.10) shows how EBITDA affects drawdown decisions. $\widehat{EBITDA}_{i,t}$ denotes the fitted value of *EBITDA* from the first-stage regression.

Table (2.11) 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 drawdowns. 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 (2.11) shows the results from our 2SLS. The coefficient on the interaction ($\widehat{EBITDA}_{i,t} \times \textit{2020:Q2}$) 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 (2.12), we study whether banks accommodated credit insurance to all the firms or 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), we show the 2SLS results. The empirical results in Table (2.12) show a negative relationship between cash flow and total credit line size at the peak of the shock in 2020:Q2. These results are robust across the 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 (2.8) (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. The COVID-19 shock is clearly different from the weather shock studied in Brown et al. (2021), as the latter is exogenous to the firm and completely idiosyncratic. At the same time, the COVID-19 shock is also exogenous but only partly idiosyncratic (i.e. it is related to the degree of firms' work flexibility). We believe that the results in this and previous sections help to better understand how different firms across countries and industries manage their short-term liquidity risk when hit by an exogenous shock. An interesting and novel aspect of our results is that banks accommodated the demand for liquidity insurance following this shock, while they did not do so during the 2008 financial crisis.

2.7 Conclusion

We studied cash flow risk management when firms are hit by a shock unrelated to their fundamentals and (in part) idiosyncratic. We showed that European firms went into a "panic borrowing" driven by an unexpected shortfall in revenue following the implementation of social distancing rules (and virus spread) across Europe. We introduced two novel risk measures to study if firms' heterogeneity to the COVID-19 shock matters. At the industry level, we showed that firms with less work flexibility drew down their credit lines, and banks accommodated the demand. At the country level, we showed that firms in countries with more strict social distancing policies did the same. To disentangle the effect of the shock on short and long-term liquidity risk management, we empirically implement a battery of econometric methodologies and quasi-natural experiments to identify the process through which the shock increased

Table 2.11. **Credit Line Drawdowns and EBITDA During the COVID-19 Crisis (OLS & 2SLS).**

This table shows the results from Equation (2.10) in OLS and 2SLS forms. The dependent variable is credit line drawdowns scaled by total assets across all columns. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the second quarter of 2020, and an indicator equal to one for highly exposed firms and zero for unexposed firms. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Fixed effects are included as indicated. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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$2020:Q2	-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 2.12. **Banks' Collaboration with Different Firm Types.**

This table shows both the OLS and 2SLS regression results of Equations (2.9) & (2.10) with an alternative dependent variable. The dependent variable is the total committed credit lines scaled by total assets across all columns. The independent variables are earnings before interest, taxes, depreciation, and amortization scaled by total assets, a time dummy indicating the second quarter of 2020, and an indicator equal to one for highly exposed firms and zero for unexposed firms. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. 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)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	2SLS
	Two Firms	Exposed Firms	Unexposed Firms	3-Way Interaction	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

the short-term firms' demand for credit insurance. Finally, 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 loan portfolio.

Also, our results make clear that a run on banks' credit lines can occur, and it suggests that it may depend on the nature of the shock and how it impacts aggregate risk (financial crisis vs COVID-19 shocks or others). 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 the shock on aggregate risk and the negative externalities for society from the run on banks' credit lines.

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Appendices

2A Description of Variables

Table 2A1. **Description of Variable**

Variable	Description	Source
Drawdown Size	Amount of the credit line that is currently used, equivalent to the difference between total and undrawn credit lines scaled by total assets.	Bloomberg
Credit Line Usage	The drawn amount of credit lines divided by the total committed amount.	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. We divide this variable by total assets.	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. Scaled by total assets.	Bloomberg
Leverage	The total amount of debt relative to total assets.	Bloomberg
Log(Assets)	The natural logarithm of total assets. Total assets include the total of all short and long-term assets as reported on the Balance Sheet.	Bloomberg
Tangible Assets	Total assets minus intangible assets, scaled by total assets.	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, scaled by total assets.	Bloomberg
Log(P/B)	The natural logarithm of the stock price to the book value per share.	Bloomberg

(Continued on next page)

Table 2A1 – continued from previous page

Variable	Description	Source
RID	The risky-investment-to-debt ratio, an index indicating the firm's solvency. Calculated as 1 - book value / (total assets - cash holdings).	Bloomberg
Distress	A measure of firm's liquidity distress. Calculated as (short-term debt - cash holdings - net income) / total assets.	Bloomberg
Free Cash Flow	The cash flow less capital expenditure, scaled by total assets.	Bloomberg
Net Income	Amount of profit the company made after paying all of its expenses.	Bloomberg
Capital Expenditure	Amount the company spent on purchases of tangible fixed assets, scaled by total assets. Note that capital expenditure is taken its absolute value.	Bloomberg
Credit Ratings	An indicator for each rating class based on S&P Issuer Rating, such as *AAA-A*, *BBB* or *Non-IG*.	Bloomberg.
Short-Term Debt	The firm's short-term debt.	Bloomberg.
High COVID Exposure	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.	ECDC Campello et al. (2020)
Log(Stringency)	The natural logarithm of the Stringency Index which records social distancing strictness across European countries. The higher Stringency Index restricts people's access to some jobs.	Our World in Data Ritchie et al. (2020)
Log(Cases)	The natural logarithm of the number of confirmed cases per million.	ECDC
Exposure	An index ranges from 0 to 1, indicating the effect of the pandemic on an industry as expressed by the labour drivers.	O*Net Dingel & Neiman (2020)
I(Exposure)	An indicator equal to 1 that the Exposure is greater than 0.75, and 0 that the Exposure is smaller than 0.3.	O*Net Dingel & Neiman (2020)

2B COVID-19 Confirmed Cases across Countries

Table 2B1. **COVID Confirmed Cases per Million.**

Country	2020:Q1	2020:Q2	2020:Q3
Austria	1038.323	1975.884	4957.475
Belgium	1100.21	5290.223	10201.336
Estonia	560.698	1496.951	2537.064
Finland	302.024	1311.237	1849.533
France	774.658	3028.092	8958.471
Germany	742.286	2329.006	3467.498
Greece	110.671	326.365	1768.727
Italy	1785.81	4061.051	5314.977
Latvia	212.389	596.611	973.361
Luxembourg	3406.739	6724.322	13309.433
Malta	320.837	1271.955	5805.433
Netherlands	778.21	2880.407	7128.681
Portugal	723.316	4095.294	7341.229
Slovenia	378.407	754.927	2684.709
Spain	2019.987	5249.254	16197.887

2C Firms' Solvency and Liquidity Constraints

Solvency-driven credit line drawdowns

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 (2C1) shows an example of a corporate balance sheet. The left-hand side shows total assets and contains cash, cash equivalent, and risky investment.[22] 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 2C1. **Balance Sheet.**

[22]Risky investment contains long-term investment and fixed assets, equal to total assets minus cash and cash equivalent, namely, total assets. This type of asset is far less liquid than cash. Investors or firms cannot convert them immediately when facing a liquidity shortfall.

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 (2C1), 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 a firm's behaviour in response to solvency risk following an unexpected shock to the risky 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 the 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 total 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 in 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 total assets, namely, the drawdown size. Subsequently, we also use credit line usage.

We employ the following model:

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

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:

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

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 total assets, the undrawn credit lines scaled by total assets, the price-to-book ratio, the tangible assets related to total assets, and the leverage ratio.

Table (2C2) shows the results. Columns (1) to (4) in Table (2C2) 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, $RID_{i,t-1} \times \textit{2020:Q2}$. Overall, columns (5) and (8) show similar results using credit line usage. The positive coefficient on RID shows that the higher the RID, the lower the solvency (i.e. the credit risk of the firm increases), and the higher the access to credit lines. On the other hand, the negative coefficient on the dummy in 2020:Q2 is interesting as it seems to suggest a negative association between credit line drawdowns and solvency risk.[23] Finally, it is indicative of the insignificant coefficients in 2020:Q3 as they imply that the effect of the shock on firms was only significant at the peak of the COVID-19 shock (2020:Q2) but did not extend to 2020:Q3. In a nutshell, lower-risk firms drew down credit lines in 2020:Q2.[24]

To explore if lower-risk firms draw down credit lines for precautionary savings, we split sampling firms into three groups: Low Risk (0%-25%), Medium Risk (25%-75%), and High Risk (75%-100%), based on their RID ratios. In Figure 2C1, We plot the changes in cash holdings in 2020:Q2 across different groups. The Low Risk group accumulates the most cash holdings during the COVID-19 shock, proving their precautionary saving purposes.

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

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

Table 2C2. **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 total assets (total assets less cash and cash equivalents). In columns (5) through (8), the dependent variables are credit line 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*). Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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)
$\text{RID}_{t-1}\times$2020:Q1		0.031				0.139		
		(0.046)				(0.165)		
$\text{RID}_{t-1}\times$2020:Q2			-0.061*				-0.199*	
			(0.032)				(0.109)	
$\text{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

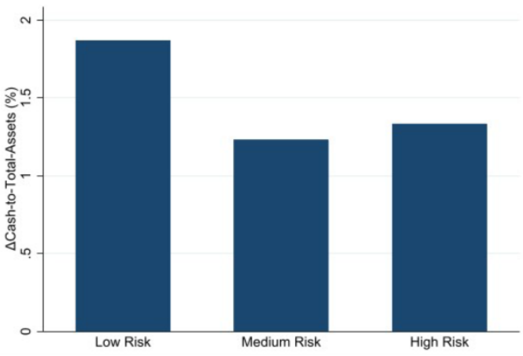

Figure 2C1. Changes in Cash Holdings by Solvency Risk.

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 Risk (25%), Medium Risk (50%) and High Risk (25%). The vertical axis shows the changes in percentage.

Credit ratings and credit line drawdowns

In Appendix 2C, we showed that, over the whole sample, there is a positive and significant association between firms' solvency risk and credit line drawdowns, but this relationship changed in 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 (2C2) 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 (2C2) 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.

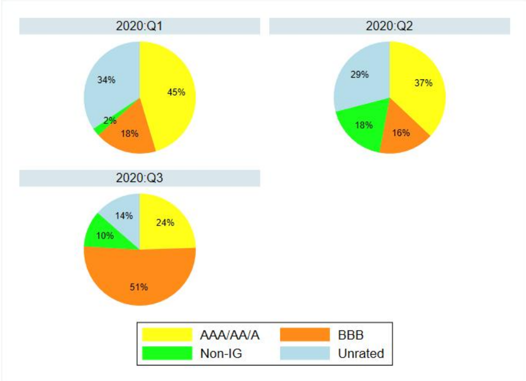

Figure 2C2. Credit Line Drawdowns by Credit Ratings.

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

Liquidity constraints and credit line 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.

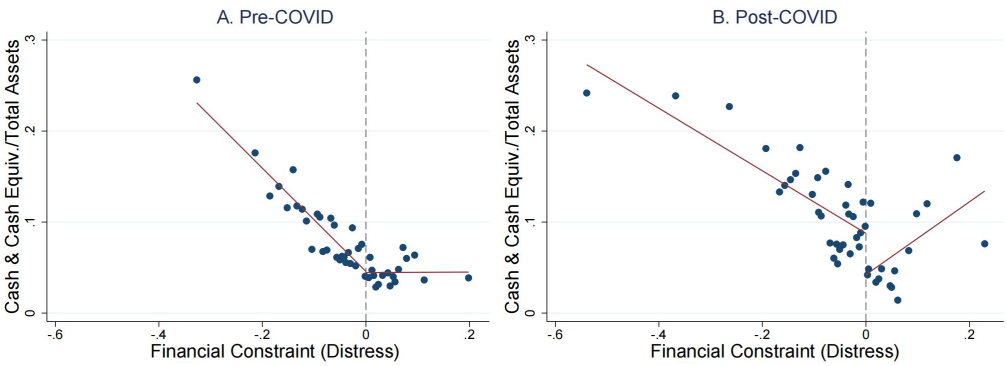

Figure 2C3. Cash Holdings versus Financial Constraint.

The diagram on the left-hand side shows a regression-discontinuity design (RD) 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 RD 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 (2C3) 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 drawdowns by including quarter dummies and using the following specification:

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

where the notations and controls are defined earlier.

Table (2C3) 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 line 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 is insignificant evidence that this also continued after 2020:Q2.

In Figure (2C4), 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.

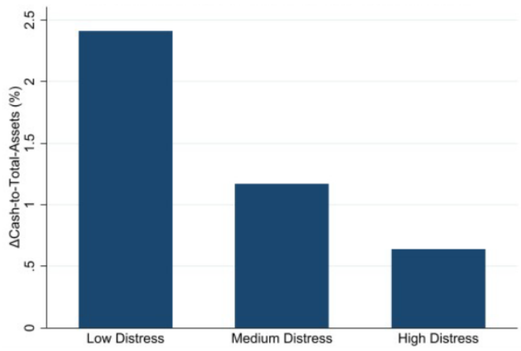

Figure 2C4. Change in Cash Holdings by Distress.

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

Table 2C3. **Drawdowns and Liquidity Distress.**

This table shows the results of the baseline models in equation (15). The dependent variables in columns (1) to (3) are credit line drawdowns scaled by total assets. The dependent variables in columns (4) to (6) are credit line usage. The independent variables are liquidity distress, cash and cash equivalents, and the interaction between distress and time dummies (*2020:Q1-Q3*). Panel A shows the interaction between distress and *2020:Q1*. Panel B shows the interaction between distress and *2020:Q2*. Panel C shows the interaction between distress and *2020:Q3*. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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$_t$×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$_t$×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$_t$×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

2D RID

In this Appendix, we provide additional support to the results in Appendix 2C and Section 2.3 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.

Table 2D1. **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. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of the price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	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 2D2. **Drawdowns on Financial Distress by Firm Types.**

The table provides the baseline regressions of credit line drawdowns on the financial distress by different firm types. In columns (1) through (4), the dependent variables are the ratio of drawdown size (*Drawdowns/total Assets*). In columns (5) through (8), the dependent variables are the usage of credit lines. The independent variables are the distress and the interaction between the distress and the *2020:Q2* dummy. Apart from the regression on the whole sample (columns (1) and (5)), the regressions are also estimated using three separate samples from firm-level clusters: the low-distress (columns (2) and (6)), the medium-distress (columns (3) and (7)), and the high-distress (columns (4) and (8)) firms. Controls include undrawn credit lines, the logarithm of total assets, the logarithm of price-to-book ratio, tangible assets, and leverage. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Firms	Low Distress	Medium Distress	High Distress	All Firms	Low Distress	Medium Distress	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

2E 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:

$$\begin{aligned} \textit{Drawdown}_{i,t} &= \beta_0 + \beta_1 \textit{EBITDA}_{i,t} + \beta_2 \textit{BelowCutoff}_{i,t} + \beta_3 \textit{EBITDA}_{i,t} \times \textit{2020:Q2} \\ &\quad + \beta_4 \textit{BelowCutoff}_{i,t} \times \textit{2020:Q2} + \beta_5 \textit{BelowCutoff}_{i,t} \times \textit{EBITDA}_{i,t} \\ &\quad + \beta_6 \textit{BelowCutoff}_{i,t} \times \textit{EBITDA}_{i,t} \times \textit{2020:Q2} + \gamma X_{i,t} + \epsilon_{i,t} \qquad (16) \end{aligned}$$

where

$$\textit{BelowCutoff}_t = \begin{cases} 1 & \textit{if Free Cash Flow}_t \in [-\lambda, 0) \\ 0 & \textit{if Free Cash Flow}_t \in [0, \lambda] \end{cases} \qquad (17)$$

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

The main parameter of interest is β_6 which we expect to be negative and statistically significant, indicating that shocks on EBITDA explain the decisions of a group of 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 (2E1) shows the individual drawdown effects based on equation (2.2) where the horizontal axis shows the bandwidth selections versus credit line 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 (2E2) shows the same effect based on the results in Table (2E1).

Table 2E1. **Alternative Regression Discontinuity Design on Drawdowns.**

This table shows an alternative regression discontinuity design of credit line drawdowns on the EBITDA. The dependent variables across all columns are *Drawdown Size*, indicating the credit line drawdowns scaled by total assets. The independent variables include *EBITDA*, earnings before interest, taxes, depreciation, and amortization scaled by total assets, *BelowCutoff*, a dummy equal to one that the firms have performance just below the cut-off point, and zero the firms are just above the cut-off point, and *2020:Q2*, a time dummy equal to one for the shock period and zero otherwise. Fixed effects are included as indicated. Columns (1), (3), (5), (7), and (9) use subsamples based on the performance just below the threshold. The rest of the 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. All variables are defined in Appendix 2A1. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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)
$\text{BelowCutoff}_{i,t}$	0.059**	0.065***	0.040*	0.043**	0.038*	0.041**	0.031	0.034*
$\times$2020:Q2	(0.025)	(0.025)	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.020)
$\text{BelowCutoff}_{i,t}$	0.906*	0.782	0.600	0.474	0.640	0.554	0.575	0.484
$\times\text{EBITDA}_{i,t}$	(0.486)	(0.493)	(0.441)	(0.447)	(0.391)	(0.395)	(0.382)	(0.386)
$\text{BelowCutoff}_{i,t}$	-3.262***	-3.349***	-2.564**	-2.446**	-2.412**	-2.370**	-2.287**	-2.281**
$\times\text{EBITDA}_{i,t}\times$2020:Q2	(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)
$\text{Undrawn CL}_{i,t}$	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

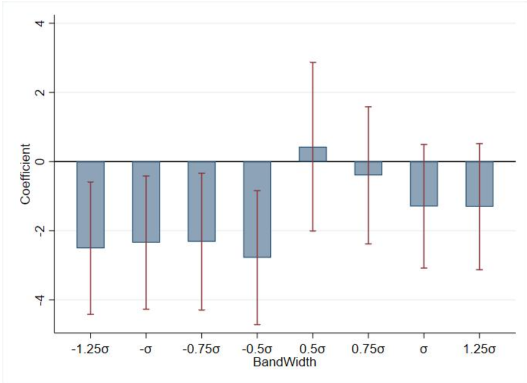

Figure 2E1. Regression Discontinuity Design 1.

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

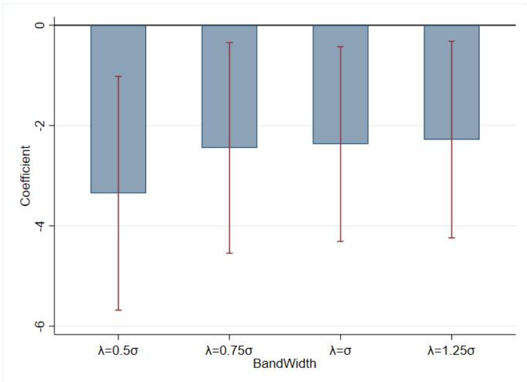

Figure 2E2. Regression Discontinuity Design 2.

The diagram shows the estimated cross-sectional differential percentage point changes in the drawdown to total assets ratio given a one percentage point change in the EBITDA to total assets ratio during the pandemic. Each cross-sectional difference evaluates the corresponding shift in drawdown decisions across the pairwise above- versus below-threshold value. The horizontal axis shows several bandwidth selections proportional to the standard deviation of the empirical distribution 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 consider even intervals around zero earnings and show 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.

Chapter 3

Precautionary Motive and Credit Lines during the COVID-19 Shock

Abstract

This paper examines the usage of credit lines by European firms during the COVID-19 crisis. We find that firms with higher credit risk drew down more credit lines for precautionary purposes. Credit line drawdowns were not associated with increased investment but were driven by firms' need to mitigate short-term credit risk. Medium-sized firms showed a higher reliance on credit lines and were more sensitive to cash flow shortfalls. The study also compares the COVID-19 crisis with the European Crisis, finding different patterns of credit line usage. The research provides insights into credit line decisions, risk management, and firm size dynamics during economic crises.

Keywords: Cash Holdings, Credit lines, COVID-19, Investment
Classification codes: G31, G32

3.1 Introduction

Was the COVID-19 crisis unique to firms using bank lines of credit? On the one hand, the literature highlights credit lines as an important source of financing corporate investment (Holmström & Tirole 2000, Campello et al. 2012, Berrospide & Meisenzahl 2015). Particularly considering the COVID-19 shock, Li et al. (2020) and Greenwald et al. (2021), for the US market, show that firms used credit lines to support investments. On the other hand, Bosshardt & Kakhbod (2020) and Acharya & Steffen (2020*b*), again for the US market, argue that firms drew down from credit lines for precautionary reasons. However, limited literature studies the European market, even though European countries are considered "bank-based economies," making the credit lines particularly relative to corporate cash holdings and investment (Campello et al. 2012). This paper aims to understand European firms' purposes for using credit lines when they experienced the COVID-19 shock.

We use quarterly data about corporate capital structure obtained from Bloomberg from the last quarter of 2018 to the third quarter of 2020. The sampling universe contains 324 European public firms with 1,159 observations, excluding all financial institutions. Did riskier firms increase credit line drawdowns more than safer firms during the COVID-19 crisis? Did firms draw down credit lines for precautionary savings or funding investment? Was the liquidity management sensitive to firm sizes? Was the pandemic shock unique to firms' liquidity management or not? These questions are the ones we investigate in this paper.

In the first part of our paper, we show that in 2020:Q2, firms withdrawing from their credit lines were low-quality and non-IG firms. This finding is consistent with experience in the US market during the pandemic (Acharya & Steffen 2020*b*) and in the European market during the Global Financial Crisis (Campello et al. 2012). Given the pandemic-induced shock, firms with higher short-term credit risk drew down more credit lines to mitigate their cash flow shortfall. Apart from credit ratings, we construct an alternative measure of short-term credit risk, the exposure-at-default ratio (EAD). Firms with higher EAD (higher credit risk) withdrew more credit lines, especially during the pandemic shock. By defining high- and low-risk firms based on the EAD, we find that high-risk firms increased their credit line usage by 41.4%, while low-risk ones inversely reduced 39.8% during the sampling period. Our empirical evidence supports that credit risk was an important factor provoking the demand for credit lines during the pandemic shock.

In the second part, we test whether firms accessed credit lines for precautionary saving or investment purposes. Using cash and cash equivalents and capital expenditure as proxies for cash savings and investment, respectively, We show that credit line drawdowns were not associated with a higher level of investment but were driven by companies' precautionary motives to offset an increase in short-term credit risk. We also examine the endogeneity problem between credit line decisions and cash saving or investment funding decisions. In this study, we use an empirical set-up based on the exogenous variations driven by the firm's undrawn credits and previous cash holdings as instruments to address the endogeneity problem between current cash and credit line decisions. We find that this problem was significant, particularly in the pandemic shock.

Next, we study whether credit lines are sensitive to firm sizes. Guney et al. (2017) find that during the crisis, small firms which are financially constrained have more reliance on revolving credit facilities than large firms. Small firms used credit lines to finance their investment during the 2007-2009 and European crises. Motivated by Guney et al. (2017), we separate firms into small-, medium-, and large-sized groups according to their total assets. We find that medium-sized firms were more allergic to the cash flow shortfall than other groups, resulting in more credit line withdrawals during the COVID-19 crisis.

Moreover, medium-sized firms held more cash via credit line drawdowns than others. We also test whether different-sized firms, especially the small ones, drew down credit lines to support investment during the COVID-19 crisis. Little evidence suggests small firms' reliance on credit lines for investment does not fit the pandemic context.

Last, we repeat our analysis of the pandemic by using the European Crisis (2009:Q4 - 2013:Q4) and investigate whether the precautionary savings still held for this period. We define the shock period in the Crisis as 2012:Q3 when the European Central Bank announced the Outright Monetary Transactions (OMT). According to our findings, little evidence supports the precautionary purpose within the European Crisis, proving the uniqueness of the COVID-19 crisis. We also find a negative relationship between credit line drawdowns and investment, providing alternative proof.

3.1.1 Related Literature

Our paper contributes to two key areas of literature. Firstly, it expands upon the existing research exploring the impact of the COVID-19 pandemic on the corporate sector. Secondly, it adds to the literature on the precautionary motive.

Most COVID-19 papers concentrate on US firms; little is known about European companies. In March 2020, the European Central Bank (ECB) initiated a program of purchasing private and public securities while relaxing collateral eligibility rules and offering financial assistance to companies (Didier et al. 2021). Several working papers, including Altavilla et al. (2021), Cascarino et al. (2022), and Jiménez et al. (2022), explore the public guarantee schemes launched by European countries for supporting corporate borrowing, but these papers focus on specific countries[1] and investigate little on firm characteristics[2]. For the supply side, Dursun-de Neef & Schandlbauer (2021) test how European banks responded to the COVID-19 shock and adjusted their lending to firms. This paper covers non-financial firms across the Euro Area and sheds some light on how the COVID-19 crisis affected European firms' liquidity management involving credit lines and cash holdings.

A large literature highlights a precautionary motive to hold cash (Almeida et al. 2004, Bates et al. 2009, Eisfeldt & Muir 2016, Acharya & Steffen 2020*b*). Acharya et al. (2012) show that the literature investigating the precautionary motive for drawing down credit lines may have produced misleading results due to the endogeneity of cash holdings with respect to credit risk. They show that some high-credit firms may behave similarly to more financially constrained firms (lower credit quality firms) when deciding to access credit lines. This is particularly true during periods when credit is abundant. The COVID-19 shock, given its unique and unpredictable aspect, is a natural laboratory for investigating the financing behaviour of financially constrained firms, as it increases firms' credit risk exogenously, as pointed out in Acharya & Steffen (2020*b*). We also contribute to this part of the literature by testing some of the predictions of the Acharya et al. (2012) model while controlling for two important aspects: COVID-19 shock and European firms.

The remaining part of our paper is organized as follows. The next section describes the data and some descriptive evidence. Section 3.3 describes the effects of credit risk on credit line drawdowns. Section 3.4 examines the precautionary purpose of drawdowns through liquidity (cash holdings and investment (capital expenditure). Section 3.5 discusses how size influences firms' access to credit lines and precautionary savings. Section 3.6 tests whether the precautionary purpose held for the European Crisis. Section 3.7 concludes.

[1]For example, Cascarino et al. (2022) study Italy and Jiménez et al. (2022) investigate Spain.

[2]For example, Altavilla et al. (2021) use the ECB database. However, they do not include corporate financial information like capital structure.

3.2 Data and Descriptive Evidence

3.2.1 Data

We collect credit lines data from Bloomberg and consider all the firms with available information between 2018:Q4 and 2020:Q3.[3] We exclude financial service companies, including banks, investment and insurance companies, private equity companies, security and commodity exchange, and wealth management companies. This study focuses on firms within the Euro Area, with 324 non-financial firms between 2018:Q4 to 2020:Q3.

We consider drawn credit lines and the total amount of committed credit lines. Specifically, total credit line data shows 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 at maturity and is equivalent to the undrawn amount of credit lines. The drawn share of 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. Appendix 3A describes the supplementary financial information, including cash and cash equivalent, tangible assets, price-to-book ratio, leverage ratio, total assets, capital expenditure, and credit ratings. Industry classification is also included based on the Bloomberg Industry Classification System (BICS).[4]

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

Table 3.1 shows the summary statistics for our sample spanning 2018:Q4-2020:Q3 with 1,157 credit facility observations. The credit line usage and undrawn capacity are 19.1 and 80.9 per cent, respectively.[5] Drawdown size, drawdowns-to-non-cash assets ratio, is about 5 per cent, and undrawn size, undrawn amount of credit line scaled by

[3]When we check Bloomberg's data of credit lines by 20 actual firms' interim reports and annual reports, we find that nearly half of the sampling firms only release their credit line information at the year-end.

[4]Standard Industry Classification (SIC) and NAICS codes are only sparsely reported by Bloomberg. Thus, this study relies on the industry classification code reported by Bloomberg.

[5]Credit line usage is given by the ratio of the drawn credit line amount to the total amount. Undrawn capacity is equivalent to one minus credit line usage.

non-cash assets, is about 12 per cent.

Table 3.1. **Summary Statistics of Regression Variables**
This table presents a description of the sample. The observations are collected from all Euro-area countries. The sampling period is from 2018:Q4 to 2020:Q3. Appendix 3A has all variable definitions.

Variable	N	Mean	Std. Dev.	Min	0.25	Median	0.75	Max
Drawdown Size	842	0.051	0.108	0.000	0.000	0.000	0.041	0.758
Credit Line Usage	844	0.207	0.297	0.000	0.000	0.000	0.387	1.000
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
EBITDA	1,055	0.028	0.031	-0.372	0.016	0.027	0.040	0.268
Undrawn CL	1,133	0.117	0.108	0.000	0.046	0.090	0.148	0.923
log(P/B)	1,130	0.532	0.834	-4.275	0.061	0.520	1.010	7.343
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
Rated	1,159	0.376	0.485	0.000	0.000	0.000	1.000	1.000
AAA-A	1,159	0.044	0.205	0.000	0.000	0.000	0.000	1.000
BBB	1,159	0.166	0.372	0.000	0.000	0.000	0.000	1.000
Non-IG	1,159	0.167	0.373	0.000	0.000	0.000	0.000	1.000
IG	1,159	0.210	0.407	0.000	0.000	0.000	0.000	1.000
Exposure at Default (EAD)	388	0.003	0.404	-6.639	0.000	0.000	0.021	1.881
High Risk	388	0.309	0.463	0.000	0.000	0.000	1.000	1.000
Low Risk	388	0.665	0.473	0.000	0.000	1.000	1.000	1.000

3.2.2 Stylized Facts about Drawdowns during the COVID-19 Crisis

External shocks, such as a liquidity shortfall, stimulate firms that appeal to external financing. The COVID-19 pandemic and the lockdown policies cause a great shock for almost all firms, especially a pause in business. Confronting such a crisis, firms may hoard cash in case of potential shocks in future. In this section, we will depict credit line drawdowns in the sampling period and then analyse the effect of different external variations, including cash flow shock and credit risks. Empirical evidence is used to support the analysis.

Revolving credit lines are the most commonly used facilities by banks to supply loans to firms. Banks commit to an amount of money that firms can access when they need it. Figure 3.1A shows drawdowns and total committed amount of credit lines for all Euro-area firms in the sample. The size of drawn credit lines was around 50 billion euros at the end of the fourth quarter of 2019, just before the beginning of the pandemic.[6] Meanwhile, the committed amount of credit lines was larger than 300 billion euros. During the pandemic, the trend has been mainly upward.

We also present the drawdown of credit lines scaled by the number of firms in each quarter. For example, 286 firms had, in total, €279.465B committed credit lines at the end of 2018:Q4, and the average committed amount should be €279.465B / 286 = €0.977B. In 2019:Q1, only 80 firms revealed a total €63.689B in committed credit lines, so the average should be €63.689B / 80 = 0.796B. The calculation also applies to the drawn amount. Appendix 3B shows more details for each quarter. Figure 3.1B also shows an upward trend of drawdown credit lines from 2019Q3 to 2020:Q3.

Figure 3.2A shows a trend in liquidity accumulation before and after the pandemic period. Specifically, the average cash holdings, including cash and cash-equivalent instruments, scaled by non-cash assets, increased sharply during the pandemic, suggesting rising cash holdings. This observation is consistent with the strand of the literature providing evidence that liquid assets tend to increase to mitigate the impact of future liquidity shocks on investment.

Theoretically, firms will hoard cash to avoid future liquidity risk and enhance future investment capacity. Figure 3.2B illustrates capital expenditure as a proxy for investment, indicating that there is limited evidence to support that firms used credit lines to support investments during the pandemic. Acharya & Steffen (2020*b*) provide empirical evidence for the US and show a corporate "dash for cash" during the pandemic mainly driven by precautionary reasons. Bosshardt & Kakhbod (2020) show similar evidence.

Corresponding with Figure 3.2A that firms accumulated cash during the pandemic, we examine the relationship between rush for cash during the pandemic and liquidity position within firms. In particular, we separate firms into two samples, low- and high-cash firms, based on the cash-to-non-cash assets ratio. Firms with this above-average ratio are defined as high-cash firms, and the rest are low-cash firms. Figure 3.3 compares the average drawdowns between high- and low-cash firms. We observe a rush for cash by low-cash firms during the pandemic period.

[6] The European Centre for Disease Prevention and Control (ECDC) documents that the first European case was reported in France on 24 January 2020. On 30 January, the World Health Organization (WHO) announced this novel coronavirus as a public health emergency of international concern.

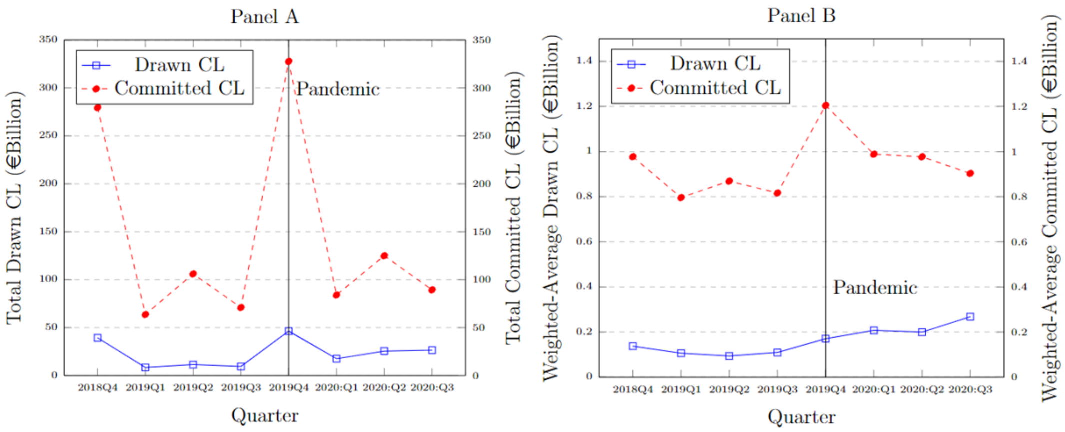

Figure 3.1. Total and Average Drawn and Committed Credit Line.

This figure plots the sum (Panel A) and average (Panel B) amount of drawn and committed credit lines between 2018:Q4 and 2020:Q3. Solid lines represent the drawn credit lines, while dashed lines represent the committed credit lines.

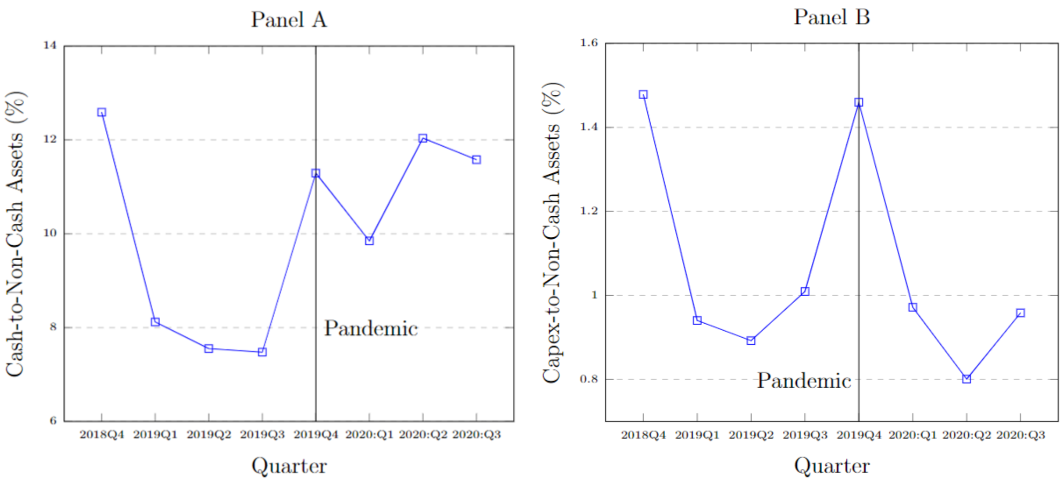

Figure 3.2. Cash Holdings and Capital Expenditure.

This figure plots the average sizes of cash holdings (Panel A) and investments (Panel B) between 2018:Q4 and 2020:Q3.

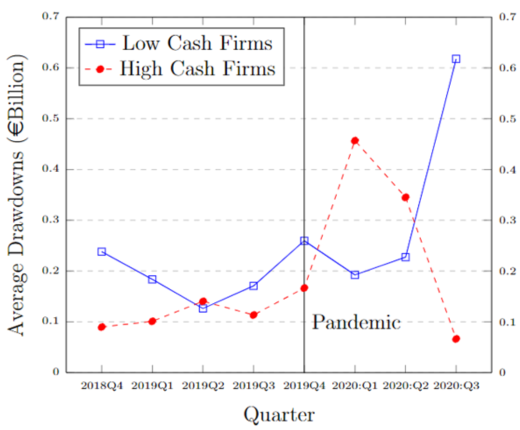

Figure 3.3. Drawdowns by Cash Sizes.

This figure plots the drawdowns in various sizes of cash holdings between 2018:Q4 and 2020:Q3. Solid lines represent low-cash firms, while dashed lines represent high-cash firms. Low-cash firms indicate firms with cash size (where cash size is the cash and cash equivalent scaled by non-cash assets) below the average. High-cash firms indicate firms with cash size above the average.

3.2.3 Liquidity Shocks and Drawdowns

The previous section provides evidence that firms rushed for cash on their credit lines during the pandemic, and low-cash firms primarily drove this result. We shed new light on why the EU firms have withdrawn from their credit lines. This context speaks to a strand of literature which has vastly focused on the US market and the 2008 financial crisis. For example, Berrospide & Meisenzahl (2015) show that firms drew down from their 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) covering only one-quarter of the pandemic period show that the US firms drew down their credit lines for precautionary reasons in anticipation of liquidity shock with heterogeneous variations across different sectors.

The aggregate statistics reveal that firms increase their cash holdings with earnings. However, we also observe that firms with low earnings tend to increase their cash holdings. Following Acharya et al. (2012), we use interest coverage ratio as a proxy for firms' financial health [7]. We define firms with interest coverage ratios above the median as high financial constraint firms and the rest as low financial constraint ones. Figure 3.4 illustrates the average cash-to-asset ratio for different deciles of the interest coverage ratio, ranging from the 10th (representing the safest) to the 1st (representing the riskiest) decile. In the figure, the solid blue line represents firms with low financial constraints, while the red dashed line shows the opposite. More specifically, firms have motives to balance the adverse implications of transitory losses by increasing their positions on safe assets such as cash and cash equivalents to counter heightened financial distress associated with their operations and net worth valuation.

Figure 3.5 shows the relation between credit line drawdown and firms' cash holdings given firms' constrain. The lowest deciles show that firms' drawdowns account for 10.19% of the firm's total assets, whereas drawdowns account for 4.71% of the total assets within the remaining deciles of cash holding distribution. The diagram on the right panel of Figure 3.5 uses an alternative measure based on firm-level credit line usage, showing a similar negative relationship. Therefore, firms facing higher financial constraints rely more on credit lines than financially unconstrained firms and firms with higher cash holdings rely less on credit lines.

Higher short-term debt and lower cash holdings and net income provide a basis to proxy firm-level financial constraints. The relation between financial constraint

[7] Interest coverage ratio is calculated as EBITDA/Interest Expense. Banks use this important covenant to monitor firms' repayment ability.

and cash holding is described in Figure 3.6 where the breakdown before and after the COVID era shows that firms with lower financial distress prefer to increase their cash holding proportionally with their performance both pre- and post-COVID eras, whilst firms decisions to build up cash balances varies depending on the shock.

The firm-level data in this context provides an additional empirical finding by showing that although firms' higher earning performance correlates positively with their cash holding balances, drawdowns wane as performance increases. Descriptive analysis results suggest that on aggregate levels, firms with higher financial constraints across all deciles of cash holding levels rely more heavily on credit line drawdowns, thus providing empirical evidence to relate drawdown decisions to financial constraints, particularly during financial distress.

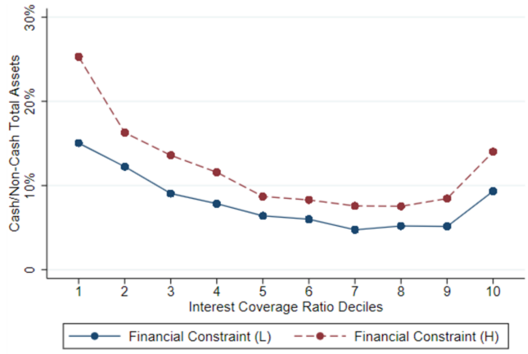

Figure 3.4. Cash Holdings versus Financial Distress.

The diagram describes the relationship between cash holding and financial distress. The horizontal axis describes deciles of the interest coverage ratio across all firms with low (solid line) and high financial constraints versus the cash to non-cash total assets. Higher (lower) interest coverage ratio deciles demonstrate higher (lower) firms' ability to meet debt liabilities at maturities, where for each decile, financially constrained firms hold higher average cash holdings relative to firms with lower financial constraints.

3.3 Credit Risks Provoke Drawdowns

3.3.1 Drawdowns by Credit Ratings: Long-term credit risk

A frequently used factor in literature for the determinant of credit lines is credit ratings (Ivashina & Scharfstein 2010; Berg et al. 2017; Chang et al. 2019 Acharya & Steffen 2020*a*; Acharya & Steffen 2020*b*). From the perspective of credit line lenders (banks), credit rating as a measurement of credit is strong evidence for evaluating a firm's repayment ability. This paper uses the S&P Global Ratings as the reference for a

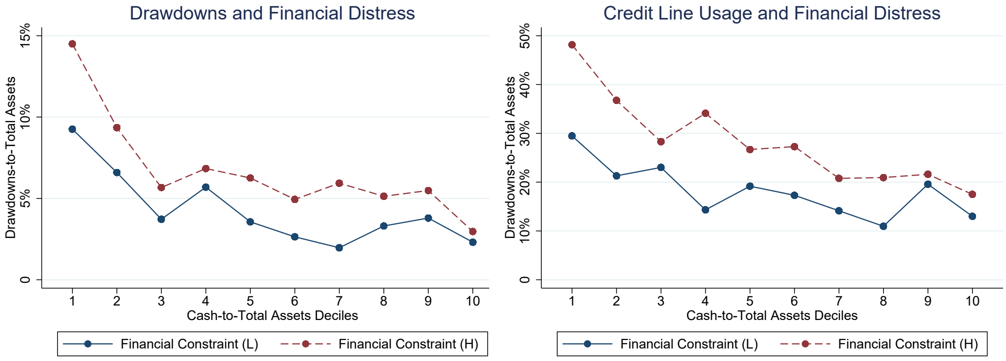

Figure 3.5. Credit Line Drawdowns versus Financial Distress.

The diagram on the left describes the relationship between drawdowns and cash holding distribution. The horizontal axis describes deciles of the cash to total asset across all firms with low (solid line) and high financial constraints versus the cash to non-cash total assets. Higher (lower) cash holding deciles demonstrate lower (higher) firm reliance on credit drawdowns, whereas, for each decile, financially constrained firms hold higher average drawdowns relative to firms with lower financial constraints. The diagram on the right describes the relationship between credit line usage and cash holding deciles. The horizontal axis describes deciles of the cash to total asset across all firms with low (solid line) and high financial constraints versus the cash to non-cash total assets. Higher (lower) cash holding deciles demonstrate lower (higher) firm reliance on credit drawdowns, whereas, for each decile, financially constrained firms hold higher average drawdowns relative to firms with lower financial constraints.

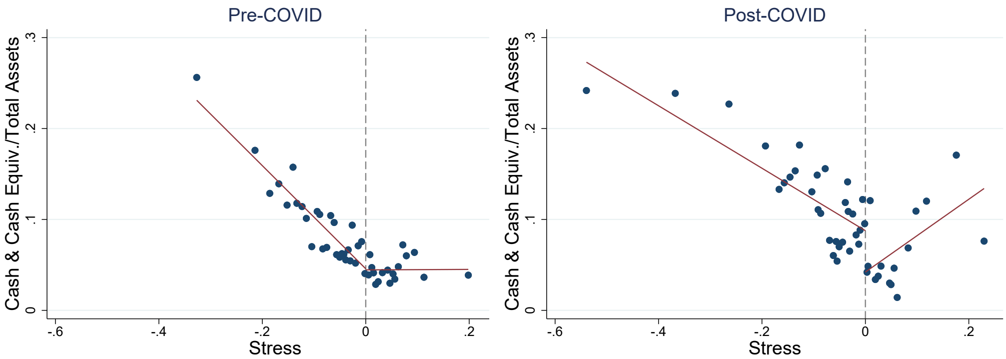

Figure 3.6. Cash Holdings versus Stress.

The scatter plots document a hockey stick-shaped relationship between firm cash holdings versus the stress metric across pre-COVID (left plot) and post-COVID (right plot) eras. Specifically, both diagrams illustrate a common negative relationship (correlations -0.79 and -0.81) between cash holdings and stress over the pre-COVID era when the stress metric is negative (high financial health indicated by liquidity). In contrast, the two diagrams illustrate contrasting relations (correlations -0.05 versus 0.21) when the stress metric is positive (low financial health indicated by liquidity). In particular, the diagrams suggest cash holding remains vastly unchanged or marginally declines when financial health improves during the pre-COVID era. In contrast, cash holding increases proportionally with financial health during the post-COVID era.

firm's credit ratings.[8] Generally, a firm with at least a BBB rating is believed to be investment-grade (IG). If it has an A, AA, or AAA rating, or a BBB rating, this firm is considered as *high quality* firm. Otherwise, a credit rating lower than BBB is vulnerable and risky for investment. Of course, many firms have no credit ratings. Thus, several questions arise: Does credit rating affect a firm's size of credit line drawdowns? What is the difference between investment- and non-investment-graded firms in terms of the size of drawdowns? What is the performance of BBB-rated firms compared to *high quality* firms?

Figure 3.7 shows the composition of credit ratings within the sampling firms. Firms are divided into AAA-A-rated, BBB-rated, non-investment-grade (Non-IG) and unrated firms.[9] Unrated firms occupy the largest, around 64%; BBB-rated firms take up about 16%, which is close to the proportion of non-IG firms at 14.3%; AAA-A-rated firms share the minority, only around 5.6%. To sum up, firms with S&P credit ratings occupy less than 40% of overall non-financial firms.[10]

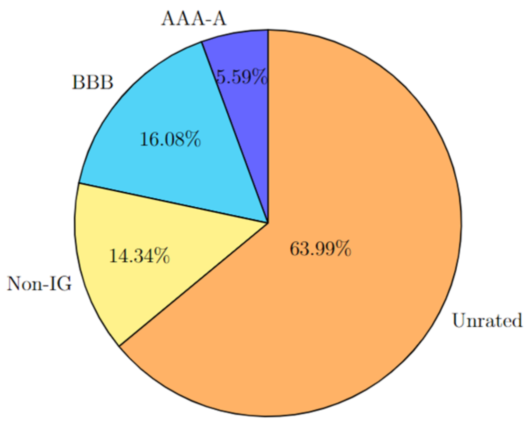

Figure 3.7. Credit Ratings Distribution.

This figure plots the distribution of credit ratings of sampling firms.

Given such a categorical method, we explore the drawdowns during the pandemic by credit ratings. Figure 3.8 illustrates weighted average drawdowns by different ratings, which can depict the withdrawal ability of each credit rating. It is significant that during the pandemic, an AAA-A-rated firm could draw down more credit lines than the rest, especially in 2020:Q1, when it could withdraw 2.7 billion euros. Other firms could only draw down credit lines below 0.5 billion euros. The BBB-rated firm ranked second, except in 2020:Q2 when it shared the same amount with a non-IG firm. Non-IG and unrated firms were similar, but the non-IG was above the unrated after 2020:Q1.

[8] Specifically, we adopt the Long-term S&P Issuer Rating that can reflect the firm's overall financial status and paying ability.

[9] AAA-A rating indicates that a firm's S&P credit rating is at least A-. BBB rating includes BBB-, BBB and BBB+ credit ratings by S&P. Non-IG rating represents the S&P credit ratings lower than BBB-. Unrated indicates that a firm does not get any S&P rating in Bloomberg.

[10] Acharya & Steffen (2020*a*) analyse a sample with only 30% rated firms in the US market. As a comparison, 40% in our data is still an acceptable amount.

It suggests that the higher the credit rating, the more drawdowns a firm can gain in the pandemic crisis. Credit rating is a significant reference that backs up credit line drawdowns.

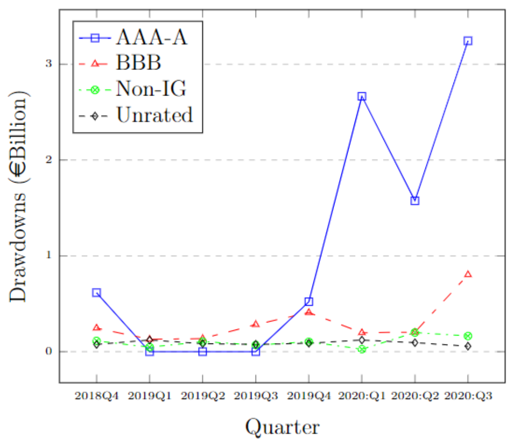

Figure 3.8. Weighted-Average Drawdowns by Credit Ratings.

This figure plots the average drawdowns across credit ratings. The solid blue line represents the drawdowns by AAA-A-rated firms across the sampling period. The red dashed line represents the BBB-rated firms. The green dashed line represents the Non-IG-rated firms, while the black dashed line represents the Unrated firms.

Instead of the absolute volume, we still use two measures to represent drawdowns as in the previous section: (i) drawdown size and (ii) credit line usage. Figure 3.9A depicts the drawdown size by credit ratings through our sampling period. In the pre-crisis, unrated firms had the largest size, followed by non-IG firms. IG firms, including the AAA-A and BBB rating classes, were at the same level. However, AAA-A-rated firms had a leap at the beginning of the pandemic, yet the rest of the rating classes experienced a decline, especially the unrated firms. It may consist of banks' highly uncertain attitude toward the pandemic. Moreover, IG firms reached higher drawdowns than before the pandemic, while non-IG and unrated firms returned to the pre-crisis level after a peak in 2020:Q2.

When it turns to Figure 3.9B, the behaviour of corporations withdrawing credit lines is reviewed from the side of credit line usage. Consistent with Figure 3.9A, Figure 3.9B reflects that both AAA-A- and BBB-rated firms climbed to a higher level than before. Non-IG and unrated firms had a remarkable increase in 2020:Q2 but then recovered the usage to the pre-crisis level in the next quarter. In short, Figure 3.9 conveys that IG firms may choose to withstand the pandemic shock by drawing down their lines of credit. Conversely, banks were willing to supply liquidity to firms with high credit ratings. Numeric data of the two plots in Figure 3.9 are presented in Table 3.2.

Two measures of drawdowns are also employed to evaluate how credit ratings determine credit line drawdowns. Firstly, we apply the drawn amount of credit lines scaled

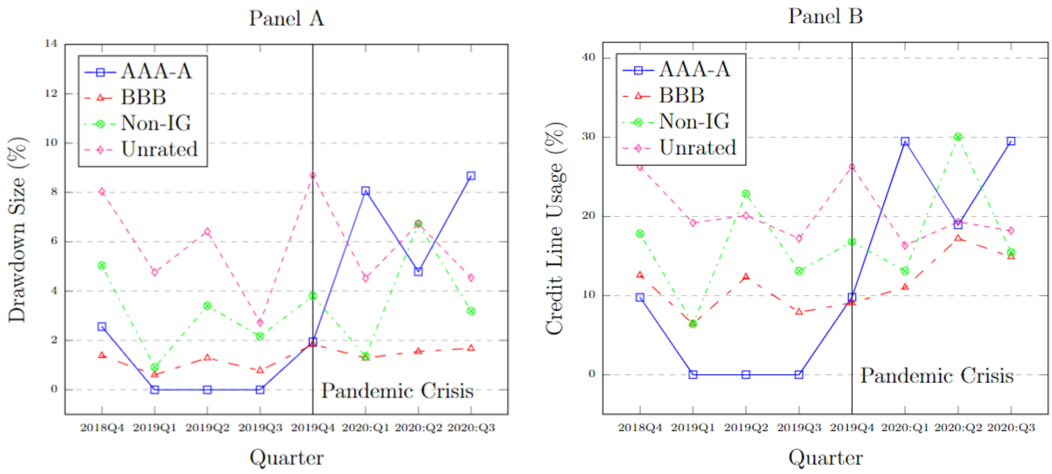

Figure 3.9. Drawdown Size and Credit Line Usage by Credit Ratings.

This figure plots the average drawdown size (Panel A) and the average credit line usage (Panel B) by various credit ratings between 2018:Q4 and 2020:Q3.

Table 3.2. **Drawdowns by Ratings in the Pandemic (2020:Q1 - 2020:Q3)**
This table presents the drawdowns by various credit ratings during the pandemic period.

	Q1-Q3 Cumulative Drawdowns (Million €)	Q1 Drawdowns (Million €)	Q1 CL Usage (%)	Q2 Drawdowns (Million €)	Q2 CL Usage (%)	Q3 Drawdowns (Million €)	Q3 CL Usage (%)
AAA-A	23.933	7.996	29.480	9.449	18.913	6.489	29.515
BBB	20.883	3.162	11.024	4.076	17.217	13.645	14.902
Non-IG	7.782	0.411	13.098	4.590	30.046	2.781	15.454
Unrated	17.068	6.061	16.330	7.414	19.309	3.593	18.188
Total	69.667	17.630	15.300	25.529	21.180	26.508	17.383

by non-cash assets, namely, the drawdown size. Secondly, we measure the drawdown behaviour by credit line usage, the drawdowns in proportions to the total committed amount of lines of credit. So, we estimate the regression within a baseline framework:

$$Drawdown_{i,t} = \alpha + \sum \beta_i Rating_i + \gamma X_{i,t-1} + \epsilon_{i,t-1} \tag{3.1}$$

where $Drawdown_{i,t}$ takes two forms: (i) drawdown size and (ii) credit line usage. $Rating_i$ is an indicator for each rating class, such as *AAA-A*, *BBB*, *Non-IG*, *IG*, or *Rated*, based on Acharya & Steffen (2020*b*). The controls, $X_{i,t}$, include the logarithm of non-cash assets, the undrawn amount of credit line scaled by non-cash assets, the price-to-book ratio, the tangible assets-to-non-cash assets ratio, and the leverage ratio.

Table 3.3 reports the regression results. In Panel A of Table 3.3, all the controls are one-quarter lagged, which tests whether the firm's financial performance in $t-1$ would affect the drawdowns in t. In other words, the corporate drawdowns were for precautionary reasons in our sampling period. Columns 1 to 3 possess the first set of the dependent variable, *Drawdown Size*. In column 1, we can see that if a firm had a credit rating, its drawdowns would be 2.5% less than that of the firm without a credit rating. In the next column, we compare the investment-graded firms (IG) and the non-investment-graded ones (Non-IG) with unrated firms.[11] Although both IG and non-IG belong to the rated cluster, IG firms (-2.8%) have slightly less drawdown size than non-IG firms (-2.3%). We want to investigate the difference between BBB and AAA-A ratings within the IG cluster. Developing on the specification in column 2, we separate the two groups of IG clusters in column 3. The BBB-rated firms have the smallest coefficient, -3.3%, while the AAA-A-rated firms have a positive but insignificant coefficient. When it turns to the second set of the dependent variable, *Credit Line Usage*, in columns 4 to 6, we can still find that rated firms have significantly smaller usage than unrated firms. The coefficient of IG firms is significant and negative, but the coefficients of non-IG ratings become insignificant. In column 6, non-IG and AAA-A ratings have insignificant coefficients, while the coefficient of BBB-rated firms is significant and negative. The number -13.5% indicates that the BBB rating has relatively low usage of credit lines among all the ratings.

We use contemporaneous controls in our model in panel B of Table 3.3. We want to test whether the decision to draw down credit lines is based on the firm's current financial performance, meaning that firms would simultaneously consider the drawdowns and their financial status. The results in Panel B show a more significant effect of credit ratings on drawdowns relative to Panel A. Setting *Drawdown Size* as the dependent variable in columns 1 to 3, the coefficients of *Rated*, *IG*, and *BBB* are more negative than Panel A, while *Non-IG* has a larger coefficient (-2.1%). *AAA-A* is still

[11] Investment grade includes credit ratings at least equal to BBB. Non-investment grade contains ratings lower than BBB class.

insignificant. Regarding the alternative set of the dependent variable, *Credit Line Usage*, the effect of drawdowns becomes less but more significant. Compared to unrated firms, rated firms had 7.2% less credit line usage. Within the rated firms, firms with the investment grade would use 10.2% fewer credit lines than unrated firms, while this number is 5.1% for non-investment-grade firms, suggesting that the IG firms had fewer usage of credit lines than the non-IG firms. Besides, AAA-A-rated firms had the least usage among all the ratings, followed by the BBB-rated firms.

Acharya et al. (2012) challenge a conventional opinion that high-cash firms are less likely to default and, therefore, have lower credit risk levels. Acharya et al. argue that "... when the risk of default increases, the firm increases its holdings of liquid assets in response. This adjustment offsets the change in risk, but only partially. As a result, a higher level of cash reflects changes across the firm's assets and liabilities but does not necessarily imply a safer firm overall." Moreover, they state, "In the presence of financing constraints, riskier firms (e.g., those with lower expected cash flows) optimally choose to maintain higher cash reserves as a buffer against a possible cash flow shortfall in the future." Therefore, raising cash holdings was the ultimate method that got firms through the pandemic crisis.

According to Acharya et al. (2012), we first plot firms' cash holdings among different credit ratings. Figure 3.10A illustrates the cash and cash equivalent scaled by non-cash assets across ratings. AAA-A-rated firms raised their cash holdings by 6% in the first two quarters of 2020, while the rest of the ratings inversely declined in Q1 and then recovered in Q2. Notably, the cash holdings of AAA-A-rated firms ranked first in Q2, but they dropped to the lowest one in Q3, back to the pre-crisis level.

In the pre-crisis period, AAA-A-rated firms maintained relatively low cash holdings. Thus, the dramatic increase in cash holdings within AAA-A ratings raises a question: What factors drove high-rated firms to rush for cash at the early stage of COVID-19? Figure 3.10B illustrates the investment, measured by capital expenditure scaled by non-cash assets, by credit ratings. From 2020:Q1 to 2020:Q2, AAA-A-rated firms reduced their investment to the lowest level among all the firms. However, they boosted the investment to the largest in Q3. Moreover, the movement was almost opposite to cash holdings in Figure 3.10A. It suggests that the reduction of investment was a salient element of hoarding cash within AAA-A-rated firms, and the effect was contemporaneous.

Acharya et al. (2012) define "risker firms" as firms with lower expected cash flows. Based on this, we measure the cash flows using EBITDA scaled by non-cash assets and plot this ratio by credit ratings in Figure 3.11A. In 2020:Q1, AAA-A-rated firms had a sharp decline by nearly 1%, which was the most. Then, AAA-A became the only rating

Table 3.3. **Credit Ratings on Drawdowns**

This table presents estimates of fixed-effect panel regressions of non-financial firms' credit line drawdowns affected by credit ratings. The dependent variables are drawdown size and credit line usage, in which the drawdown size is the drawn amount of credit lines scaled by non-cash assets, and the credit line usage is the drawn amount divided by the total amount of credit lines. The independent variable is: rated firms, a dummy equal to one that firms have credit ratings; investment-graded firms (IG), a dummy equal to one that firms have credit ratings above BB; non-investment-graded firms (Non-IG), a dummy equal to one indicating firms with ratings equal or below BB; AAA-A-rated firms, a dummy indicating firms with high ratings (above BBB); BBB-rated firms, a dummy indicating firms with BBB rating. Controls include undrawn size, the undrawn amount of credit lines scaled by non-cash assets; tangibility, the tangible scaled by non-cash assets; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets; leverage ratio, the total debt divided by total assets. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Drawdown Size			Credit Line Usage		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Specification						
Rated	-0.025**			-0.083**		
	(0.011)			(0.037)		
IG		-0.028**			-0.122***	
		(0.014)			(0.045)	
Non-IG		-0.023*	-0.024*		-0.057	-0.056
		(0.013)	(0.013)		(0.040)	(0.040)
AAA-A			0.018			-0.028
			(0.027)			(0.084)
BBB			-0.033**			-0.135***
			(0.014)			(0.046)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes			
Time FE	yes	yes	yes	yes	yes	yes
Observations	391	391	391	384	384	384
Adjusted R^2	0.048	0.045	0.054	0.017	0.020	0.022
Panel B: Contemporaneous Specification						
Rated	-0.029***			-0.072***		
	(0.010)			(0.026)		
IG		-0.041***			-0.102***	
		(0.012)			(0.032)	
Non-IG		-0.021*	-0.021*		-0.051*	-0.051*
		(0.011)	(0.011)		(0.029)	(0.029)
AAA-A			-0.025			-0.104**
			(0.018)			(0.050)
BBB			-0.045***			-0.101***
			(0.012)			(0.033)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes			
Time FE	yes	yes	yes	yes	yes	yes
Observations	816	816	816	800	800	800
Adjusted R^2	0.177	0.179	0.180	0.039	0.041	0.040

with an increase in cash flow in Q2 when the rest of the ratings kept decreasing. It may imply that AAA-A-rated firms were more concerned about their cash flows than others. They worried about their increased risk of default, or worse, downgrading. We, therefore, apply the interest coverage ratio, the EBITDA divided by the interest expenses, to measure credit risk, which is also a frequently used covenant by banks. Figure 3.11B illustrates the interest coverage ratios through all the ratings. The AAA-A-rated firms ranked last in the first quarter of 2020, showing that AAA-A-rated firms suffered credit risk the most at the beginning of the pandemic. Then, they dramatically increased the ratio by 200% in Q2. It is evidence that AAA-A was more vulnerable and sensitive to (potential) cash flow shortfall than other ratings. Besides, the increase in cash flow in Q2 also made the cash holdings peak in the same period.

Returning to Figure 3.10A, we can find that the cash reserve of AAA-A-rated firms increased by nearly 4% in 2020:Q1, partly due to a 0.7% decrease in investment (Figure 3.10B). However, the cash flow dropped by 0.84% in Q1, which covered the savings from the investment. Combining with Figure 3.9A, a 6% increase in drawdown size (credit line drawdowns scaled by non-cash assets) became the dominant contribution to hoarding cash. Thus, our theoretical argument is summarized: Confronting the default risk increased at the beginning of the pandemic, and AAA-A-rated firms increased their cash holdings in response. Although the investment was reduced to the government's policy, the savings were offset by the decrease in cash flows. Consequently, the firms could only rely on the credit line drawdowns to hoard a higher level of cash.

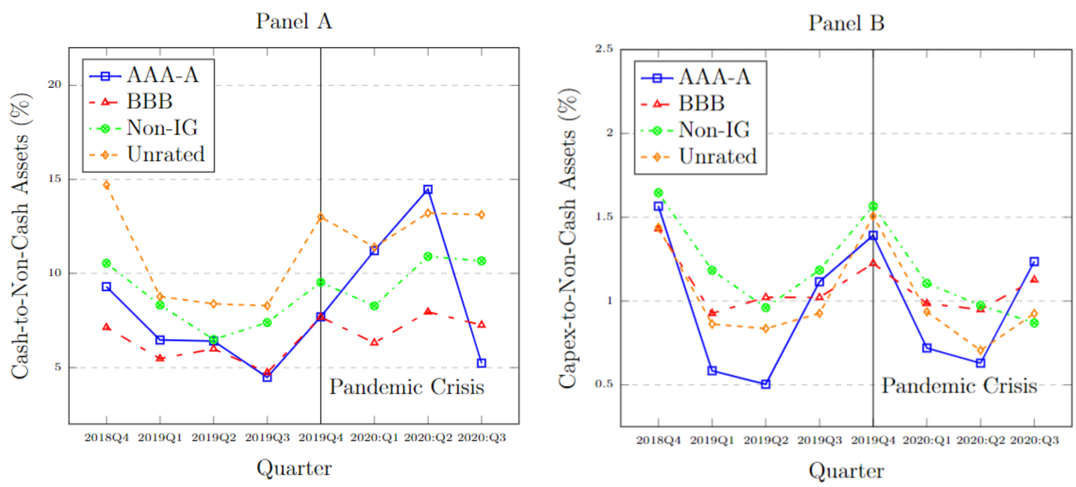

Figure 3.10. Cash Holdings and Investment by Credit Ratings.

This figure plots the average cash size (Panel A) and the average investment (Panel B) across various credit ratings between 2018:Q4 and 2020:Q3.

Figure 3.11. Cash Flow and Interest Coverage Ratio by Credit Ratings.

This figure plots the cash flow and interest coverage ratio by credit ratings. The left plot depicts the cash flow measured by EBITDA divided by non-cash assets (total assets less cash and cash equivalents), while the right plot illustrates the interest coverage ratio measured by EBITDA divided by interest expenses.

3.3.2 Exposure at default (EAD) and Drawdowns: Short-term credit risk

In the previous section, we examine the determinant of credit ratings on firms' credit line drawdowns. Since credit ratings are generally defined by third parties like Standard & Poor's (S&P), it is necessary to use an alternative measure of a firm's credit risk based on its corporate disclosure.

We use exposure at default (EAD) as a proxy for corporate credit risk. With the probability of default (PD) and loss given default (LGD), EAD is favourable for banks to measure expected loss or unexpected loss that banks must hold capital. Banks' exposure to firms' default risk inevitably affects both undrawn and drawn credit lines. Although there is no explicit calculation of EAD in the Basel II/III Accord, researchers regard that the Credit Conversion Factor (CCF), based on historical data, is the core of modelling EAD (Valvonis 2008, Tong et al. 2016). Valvonis (2008) emphasizes that the new EU Capital Adequacy Directive (CAD) indicates the drawn amount of credit lines at present, and the estimation of future drawdowns on the undrawn amount constitutes the value of EAD, which meets our research context of European firms.

Meanwhile, CCF describes the percentage of current undrawn credit lines that may withdraw at default. Thus, modelling EAD is basically about modelling CCF. Given the definition, CCF has an expression:

$$CCF = \frac{Drawn\ Credit\ Lines - Previous\ Drawn\ Credit\ Lines}{Previous\ Undrawn\ Credit\ Lines}$$

Thus, EAD, in our case, has a formulation, given by:

$$EAD = \textit{Drawndown Size} + (\textit{CCF} \times \textit{Undrawn Size})$$

where *Drawndown Size* is the drawn amount of credit lines scaled by non-cash assets. *Undrawn Size* is the undrawn amount scaled by non-cash assets.

As banks are interested in firms' credit, EAD is one of the measures by which banks decide the committed or drawn amount of credit lines. To assess the effect of EAD, we still apply the drawdown size and the credit line usage for dependent variables. The estimation is based on the panel regression as follows:

$$\begin{aligned} \textit{Drawdown}_{i,t} &= \alpha + \beta_1 EAD_{i,t} + \beta_2(EAD_{i,t} \times \textit{2020:Q2}) \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.2}$$

where $\textit{Drawdown}_{i,t}$ represents both drawdown size and credit line usage. $EAD_{i,t}$ indicates the exposure at default. *2020:Q2* is a dummy representing the time when liquidity shock happens. The controls $X_{i,t}$ contain the undrawn credit lines relative to non-cash assets, the logarithm of non-cash assets, the tangible assets scaled by non-cash assets, the price-to-book ratio, and the leverage ratio.

Table 3.4 shows the estimates. Columns (1) and (2) use the same dependent variable, drawdown size, and columns (3) and (4) adopt the usage of credit lines as the dependent variable. The significant and positive coefficient on EAD, β_1, shows that if a firm has more default risk, it tends to withdraw more credit lines. According to the coefficient of the interaction $EAD_{i,t} \times \textit{2020:Q2}$, β_2, the tendency to drawdowns is enormously strengthened in the pandemic shock. In column (4) of Table 3.4, credit line usage increases by 69.8% in the shock.

Next, we separate samples into groups to investigate whether different default exposure levels affect firms' drawdown decisions, especially the highest and lowest ends. Compared with low-exposed firms, we expect firms highly exposed to default risk may rush for more cash via credit lines. To do so, we defined the firms with the average EAD at the top tertile (66.7% - 100%) as *High Risk*, while the ones at the bottom tertile (0% - 33.3%) as *Low Risk*. We construct the following panel regression model:

$$\begin{aligned} \textit{Drawdown}_{i,t} &= \alpha + \beta_1 \textit{Default Rating}_{i,t} + \beta_2 \textit{Default Rating}_{i,t} \times \textit{2020:Q2} \\ &\quad + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.3}$$

where $\textit{Drawdown}_{i,t}$ represents either drawdown size or credit line usage defined as before. The indicator $\textit{Default Rating}_i$ contains: 1) *High Risk*, the firm with high exposure to default risk, and 2) *Low Risk*, the opposite. *2020:Q2* is a dummy representing the shock period. $X_{i,t}$ indicates the controls as before.

Table 3.5 displays the results of the specification. The coefficient on the dummy (*High Risk*) is statistically significant and positive, similar to the ones in Table 3.4. Meanwhile, the coefficient on the interaction term ($HighRisk_t \times$ *2020:Q2*) also shows significant and positive, indicating an extra credit line drawdown in highly exposed firms during the COVID-19 shock. On the contrary, the coefficient on the dummy (*Low Risk*) carry a statistically significant and negative sign. It suggests that firms with good financial health (low default risk) reduce their reliance on banks' credit lines. This reliance became even weaker during the COVID-19 shock, according to the negative coefficient on the interaction ($LowRisk_t \times$ *2020:Q2*). An interesting finding is a significant and positive coefficient on firms' leverage ratios ($Leverage_t$), which shows a positive association between leverage and credit line drawdowns. It implied that high-levered firms withdrew more credit lines than low-levered ones during the COVID-19 shock, even though they had already suffered a higher default risk. Nevertheless, the low-levered firms reduced their debt level to protect themselves from default risk during the shock.

3.4 Precautionary Saving Purpose: Multivariate Evidence

This section will explore the precautionary saving purpose of credit line drawdowns. At first, we estimate the effect of drawdowns on cash holdings, providing empirical evidence. In the next stage, we discover the precautionary purpose in an opposite way, examining whether firms use drawdowns for investment purposes.

3.4.1 How Large Is the Drawdown Effect on Savings?

Research indicates that the firm's rising credit line use fulfils the demand for cash (Sufi 2009, Ivashina & Scharfstein 2010). Furthermore, Ivashina & Scharfstein (2010) believe that the credit line drawdown is for the future need for cash. In other words, the effect of drawdowns on cash hoarding lag. Sufi (2009) argues that the drawdown is for the contemporary cash demand. This section will examine the debate and evaluate both the lagged and contemporaneous effects of drawdowns.

Table 3.4. **Exposure at Default on Drawdowns**

This table presents estimates of fixed-effect panel regressions of non-financial firms' credit line drawdowns affected by exposure at default. The dependent variables are drawdown size (Columns (1) - (2)), the drawn amount of credit lines scaled by non-cash assets, and credit line usage (Columns (3) - (4)), the drawn amount divided by the total amount of credit lines. The independent variables are exposure at default (EAD), a measure of corporate default risk; 2020:Q2, a dummy variable that equals one indicating the time when the postponing effect of the pandemic happens. Controls include undrawn size, the undrawn amount of credit lines scaled by non-cash assets; tangibility, the tangible scaled by non-cash assets; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets; leverage ratio, the total debt divided by total assets. Appendix 3A contains all variable definitions. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Drawdown Size		Credit Line Usage	
	(1)	(2)	(3)	(4)
EAD_t	0.055***	0.044***	0.111***	0.089***
	(0.009)	(0.009)	(0.034)	(0.034)
$EAD_t \times$2020:Q2		0.339***		0.698***
		(0.049)		(0.187)
Undrawn CL_t	0.079*	0.108***	-0.610***	-0.551***
	(0.041)	(0.039)	(0.152)	(0.150)
$\log(P/B)_t$	-0.003	-0.001	-0.034	-0.029
	(0.006)	(0.006)	(0.021)	(0.021)
$\log(\text{Assets})_t$	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.008)	(0.008)
Tangible Assets_t	-0.024	-0.030*	-0.078	-0.091
	(0.016)	(0.015)	(0.060)	(0.059)
Leverage_t	0.047*	0.037	0.097	0.076
	(0.028)	(0.026)	(0.102)	(0.100)
Industry FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes
Observations	375	375	375	375
Adjusted R^2	0.104	0.211	0.094	0.126

Table 3.5. **High and Low Default Risk on Drawdowns**

This table presents estimates of fixed-effect panel regressions of non-financial firms' credit line drawdowns affected by default risk. The dependent variables are drawdown size (Columns (1) - (4)), the drawn amount of credit lines scaled by non-cash assets, and credit line usage (Columns (5) - (8)), the drawn amount divided by the total amount of credit lines. The independent variables are *High Risk*, a dummy that equals to one indicating the risky firms with exposure at default (EAD) at the top tertile (66.7% - 100%); *Low Risk*, a dummy equal to one indicating the safe firms with the EAD ratio at the bottom tertile (0% - 33.3%). *2020:Q2* is a time dummy indicating the shock period. Controls include undrawn size, the undrawn amount of credit lines scaled by non-cash assets; tangibility, the tangible scaled by non-cash assets; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets; leverage ratio, the total debt divided by total assets. Appendix 3A contains all variable definitions. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Drawdown Size				Credit Line Usage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Risk$_t$	0.104***	0.097***			0.429***	0.414***		
	(0.007)	(0.007)			(0.020)	(0.022)		
High Risk$_t$		0.043**				0.094*		
×2020:Q2		(0.018)				(0.055)		
Low Risk$_t$			-0.098***	-0.092***			-0.411***	-0.398***
			(0.007)	(0.007)			(0.020)	(0.022)
Low Risk$_t$				-0.041**				-0.085
×2020:Q2				(0.018)				(0.055)
Undrawn CL$_t$	0.033	0.038	0.044	0.050	-0.705***	-0.695***	-0.659***	-0.648***
	(0.033)	(0.033)	(0.034)	(0.034)	(0.101)	(0.100)	(0.104)	(0.104)
log(P/B)$_t$	0.007	0.006	0.009*	0.009*	0.006	0.005	0.015	0.014
	(0.005)	(0.005)	(0.005)	(0.005)	(0.015)	(0.014)	(0.015)	(0.015)
log(Assets)$_t$	-0.001	-0.002	-0.001	-0.001	-0.011**	-0.011**	-0.008	-0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
Tangible Assets$_t$	0.010	0.007	0.002	0.001	0.066	0.060	0.035	0.032
	(0.013)	(0.013)	(0.014)	(0.014)	(0.041)	(0.041)	(0.042)	(0.042)
Leverage$_t$	0.045**	0.045**	0.047**	0.047**	0.136**	0.135**	0.146**	0.144**
	(0.022)	(0.022)	(0.023)	(0.023)	(0.068)	(0.068)	(0.070)	(0.070)
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	375	375	375	375	375	375	375	375
Adjusted R^2	0.422	0.430	0.389	0.396	0.590	0.592	0.565	0.567

Empirical analysis of precautionary saving purpose

Similarly, we follow the same pattern in the previous section and establish a model with an expression as:

$$\begin{aligned} Cash_{i,t} &= \alpha + \beta_1 Drawdown_{i,t-1} + \beta_2 (Drawdown_{i,t-1} \times \mathit{2020{:}Q2}) \\ &\quad + \gamma X_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{3.4}$$

where *Cash* is defined as the cash and cash equivalent scaled by non-cash assets. *Drawdown* refers to the drawdown size equal to the drawn credit lines relative to non-cash assets. *2020:Q2* is a dummy representing the period when the liquidity shock occurred. Additional controls include the undrawn credit lines in proportion to non-cash assets, the logarithm of non-cash assets, the price-to-book ratio, the tangible assets scaled by non-cash assets, and the leverage.

To test the assumption of precautionary cash hoarding, we assess whether drawdowns in $t-1$ enhance cash in t. In comparison, we also test the simultaneous effect of drawdowns on cash holdings by testing whether drawdowns in t affect cash in t. The key interest is the interaction between drawdowns and shock dummy, reflecting whether the effect of drawdowns had an impact on cash hoarding in the crisis.

Table 3.6 reports the regression results. Columns 1 and 2 report the OLS estimation of equation (3.4). In panel A, the coefficient of *Drawdown Size* is significant and positive, while the coefficient in panel B is positive but insignificant. This situation suggests that although the increase in drawdowns would increase firms' cash holdings, the purpose of drawing down the credit line was for precautionary demand. Beside, the coefficients of interaction $Drawdown_{i,t-1} \times \mathit{2020{:}Q2}$ are insignificant. It seems that the occurrence of liquidity shock did not affect the impact of drawdowns.

Endogenous problem and explanation

The remaining committed credit lines and the cash holdings in the previous period are exogenous to the current drawdowns. If we assess the endogeneity problem, two kinds of financing abilities may be important instrumental variables. In the first stage, we study the lagged effect of drawdowns on cash holdings. Thus, the undrawn capacity in $t-2$, measured by the undrawn credit lines relative to the committed credit lines, and the cash holdings in $t-2$ are exogenous to the drawdown size in $t-1$ and the cash holdings in t. Columns 3 to 6 in panel A of Table 3.6 show the results of IV regression. Conditional on the undrawn capacity in columns 3 and 4, *Drawdown Size* has a significant, positive coefficient. The coefficient is twice the OLS estimation (columns 1 and 2), indicating an enhanced effect of drawdowns conditional on the undrawn capacity. In columns 5 and 6, the instrumental variable turns to the cash holdings. There is a remarkable increase in the coefficient of *Drawdown Size*, around twenty times the OLS estimator. When it comes to the interaction *Drawdown Size* × *2020:Q2*, the undrawn capacity as an instrumental variable does not make the coefficient of the interaction significant (column 4). However, the coefficient of the interaction conditional on the cash holdings is significant and negative in column 6.

Next, we evaluate the simultaneous effect of drawdowns on cash holdings within the IV regression model. Panel B of Table 3.6 presents the result of *Drawdown Size* in t. Using undrawn capacity as an instrument (columns 3 and 4), we can see that the coefficient of *Drawdown Size* is significant and positive. However, the number is smaller than the one in panel A, suggesting a reduced volume of the effect. When the specification is conditional on the previous cash holdings, the coefficient of *Drawdown Size* is enhanced enormously. Besides, the interaction *Drawdown Size* × *2020:Q2* is still insignificant if the instrument variable is the undrawn capacity. At the same time, it becomes significant and negative using cash holdings in the previous period as an instrument.

In conclusion, Table 3.6 clarifies that firms drew down their credit lines to raise cash instead of maintaining investment. They used credit line drawdowns as a precautionary measure against liquidity risk. If we control for the drawdown effect's endogeneity, the cash hoardings' acceleration reduces when the liquidity shock appears.

3.4.2 Do Firms Use Drawdowns for Investment Purpose?

Empirical test of investment

In the previous section, we discuss the rise of drawdowns for precautionary saving. We now test whether firms draw down their credit lines for investment.

To test the association between drawdown and investment, we construct a fixed effect panel regression model. The model has the following specification:

$$\begin{aligned} Investment_{i,t} &= \alpha + \beta_1 Drawdown_{i,t-1} + \beta_2 (Drawdown_{i,t-1} \times \mathit{2020{:}Q2}) \\ &\quad + \gamma X_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{3.5}$$

where *Investment* is defined as the percentage of capital expenditure to non-cash assets. Capital expenditure is transferred into the absolute value. *Drawdown*, like section

Table 3.6. **Cash Holdings and Drawdowns**

This table presents the results of panel regression of firms' cash holdings. The dependent variables across all columns are the cash holding size equal to cash and cash equivalent scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are drawdown size, the drawn amount of credit lines scaled by non-cash assets; 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Specification						
Drawdown Size$_{t-1}$	0.137***	0.134***	0.333**	0.378**	2.557***	3.075***
	(0.044)	(0.046)	(0.136)	(0.173)	(0.758)	(1.023)
Drawdown Size$_{t-1}$×2020:Q2		0.036		-0.183		-2.825**
		(0.150)		(0.231)		(1.092)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	385	385	299	299	310	310
Adjusted R^2	0.421	0.419	0.296	0.283	-3.778	-4.925
Panel B: Contemporaneous Specification						
Drawdown Size$_t$	0.017	0.021	0.250***	0.271**	3.888***	6.660*
	(0.029)	(0.031)	(0.092)	(0.108)	(1.361)	(3.417)
Drawdown Size$_t$×2020:Q2		-0.031		-0.135		-6.209*
		(0.083)		(0.134)		(3.282)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	774	774	370	370	384	384
Adjusted R^2	0.480	0.479	0.386	0.383	-11.798	-26.267

3.2.3, indicates the drawn amount of credit lines scaled by non-cash assets. A dummy, *2020:Q2*, represents the time when the liquidity shock occurred. As controls, we include the undrawn credit lines scaled by non-cash assets, the natural logarithm of non-cash assets, the price-to-book ratio, the tangible assets relative to non-cash assets, and the leverage.

Columns 1 and 2 in Table 3.7 report the estimation of equation (3.5). Also, the drawdown variable and the controls are taken into two forms: the one-period lagged and the contemporaneous ones. The comparison between these two forms explores whether the investment is determined by the previous or the recent drawdowns. In panel A of Table 3.7, the coefficient of the drawdown size in $t-1$ is significantly negative, indicating that, on average, the firm's previous drawdowns shrink the size of capital expenditure. The interaction of drawdowns and liquidity is positive but insignificant, suggesting that drawdowns might not boost investment in the shock. In panel B, we consider the simultaneous effect of drawdowns on investment. This is because firms may jointly decide the size of drawdowns and investments.[12] Accordingly, the coefficient of drawdown size in t is significant and negative. As the coefficient is larger than the one in $t-1$ in panel A ($-0.013 > -0.015$), it implies that the contemporaneous effect is weaker than the lagged effect. Also, the coefficient of the interaction is positive but insignificant.

Endogenous problem and explanation

Whether the drawdown variable lags or not, it has a significant and parallel impact on the investment. In other words, lagged drawdown variables may lose their power to alleviate potential endogeneity. In the next step, we extend the model by adding instrumental variables to deal with the endogenous problem.

The chosen instruments reflect the firm's financing ability against liquidity risk. This ability may come from external or internal sources. External source, in this case, refers to undrawn capacity. Undrawn capacity, or credit line availability, is the remaining amount proportional to the total amount of committed credit lines. The covenants of credit line agreements predetermine it, reflecting lender requirements (Berrospide & Meisenzahl 2015). Undrawn capacity is generally exogenous to a firm's control or bargaining power. Thus, it is a financing constraint for credit line drawdowns. Our model estimates the effect of drawdowns conditional on the remaining committed credit lines. The internal source refers to cash holdings. Cash holdings consist of cash balance and short-term, highly liquid investment, enabling firms to access their money

[12] A reminder is that firms may simultaneously consider drawdowns, cash and investment. It is possible that considering the simultaneous effect of drawdowns will lead to an endogeneity problem.

quickly. However, there is always a trade-off of hoarding cash: hoarding too little cash cannot meet emergency funding needs. At the same time, too many cash hoardings are detrimental because they sacrifice the investment opportunity of more profitable but long-term projects. Therefore, the firm's decision on the cash amount is path-dependent in common. As a way of raising cash, credit line drawdowns are naturally restricted by the firm's cash holdings. Thus, we construct a cash-to-non-cash assets ratio as another instrumental variable.

Consistent with section 3.4.2, we discuss the endogeneity problem in two scenarios. In the first scenario, the specification explores the assumption that the undrawn capacity (or cash holdings) in $t-2$ is exogenous to capital expenditure in t and merely influences the drawdowns in $t-1$. In the second scenario, the specification assumes that the undrawn capacity (or cash holdings) in $t-1$ affects the drawdowns in t, but it is exogenous to capital expenditure in t. These two scenarios might be arbitrary but effective in revealing the endogeneity. Besides, Sargan-Hausen tests confirm the validity of using these instruments.[13]

Columns 3 to 6 in Table 3.7 document the results of IV regression. Using the undrawn capacity as an instrument, the coefficient of drawdown size in $t-1$ is triple the one in the OLS estimation. As for cash holdings, the coefficient of drawdown size in $t-1$ becomes nearly tenfold. Specifically, introducing cash holdings makes the interaction of the drawdowns and the shock dummy significant and positive. When we consider the simultaneous effect of drawdowns, introducing the undrawn capacity in $t-1$ as an instrument enlarges the coefficient of drawdowns more than triple. Cash holdings in $t-1$ also enhance the effect of drawdowns, but the coefficient becomes insignificant if the interaction, *Drawdown Size*$\times$*2020:Q2*, is included. However, β_2, the coefficient, is significant and positive when we apply undrawn capacity in $t-1$ as an instrumental variable.

Overall, Table 3.7 suggests that the firm's drawdowns do not support investment. This suggestion corresponds to the finding of Bosshardt & Kakhbod (2020), but it might contradict what Berrospide & Meisenzahl (2015) finds. An explanation is that the higher the drawdowns, the more likely firms choose to hoard liquidity against long-term liquidity risk; the lower the drawdowns, the more likely firms merely use drawdowns to fulfil short-term, petty investment needs. This situation may be reinforced if the credit line lenders tighten the credit standard.

[13] All the Sargan statistics of two instrumental variables are less than 0.001 in two scenarios. Besides, the Cragg-Donald Wald F statistics also support the validity of the instruments.

Table 3.7. **Capital Expenditure and Drawdowns**

This table presents the results of panel regression of firms' investment. The dependent variables across all columns are the investment size equal to capital expenditure scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are drawdown size, the drawn amount of credit lines scaled by non-cash assets; 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lagged Specification						
Drawdown Size$_{t-1}$	-0.015**	-0.015**	-0.048***	-0.057***	-0.120**	-0.142**
	(0.006)	(0.006)	(0.017)	(0.021)	(0.051)	(0.065)
Drawdown Size$_{t-1}$×2020:Q2		0.005		0.040		0.119*
		(0.021)		(0.027)		(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	363	363	283	283	291	291
Adjusted R^2	0.185	0.182	0.017	-0.024	-0.748	-0.986
Panel B: Contemporaneous Specification						
Drawdown Size$_t$	-0.013***	-0.014***	-0.043***	-0.049***	-0.281**	-0.515
	(0.004)	(0.004)	(0.013)	(0.015)	(0.125)	(0.350)
Drawdown Size$_t$×2020:Q2		0.004		0.041**		0.474
		(0.010)		(0.018)		(0.328)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	704	704	352	352	363	363
Adjusted R^2	0.164	0.163	-0.021	-0.023	-6.434	-16.275

3.5 Precautionary Saving Purpose and Firm Sizes

This section will focus on firms' behaviour based on their sizes. Firstly, we will explore whether the effect of liquidity shock varies among firm sizes. Then, we will examine the influence of firm size on firms' investment and savings.

3.5.1 Cash Flow on Drawdowns by Firm Sizes

We define three types of firm size in our sample based on total assets. *Small Firm* has total assets of less than 1 billion euros. *Medium Firm* possesses total assets of over 1 billion euros but less than 10 billion euros. *Large Firm* takes the rest, with over 10 billion assets. Accordingly, we separate the sample into three subsamples derived from firm sizes. Then, we run the following specification:

$$\begin{aligned} Drawdowns_{i,t} &= \alpha + \beta_1 EBITDA_{i,t-1} + \beta_2 (EBITDA_{i,t-1} \times \mathit{2020{:}Q2}) \\ &\quad + \tau_i + \gamma X_{i,t-1} + \epsilon_{i,t-1} \end{aligned} \tag{3.6}$$

where *Drawdowns* has two definitions: credit line drawdowns scaled by non-cash assets and the drawn scaled by total committed credit lines. *EBITDA*, earnings before interest, taxes, depreciation, and amortization, indicates cash flow, scaled by non-cash assets. A dummy, *2020:Q2*, represents the time when the liquidity shock occurred. τ_i represents three subsamples including *Small*, *Medium*, and *Large Firms*. As controls, we include the undrawn credit lines scaled by non-cash assets, the natural logarithm of non-cash assets, the price-to-book ratio, the tangible assets relative to non-cash assets, and the leverage.

Results are shown in Table 3.8. Columns (1) to (4) in Table 3.8 use drawdown size as a dependent variable, while columns (5) - (8) use credit line usage. Given the previous cash flow shortfall, the larger the firms, the more credit lines they draw down (columns (1) - (4) in Panel A). The trend is inconspicuous for the usage (columns (5) - (8) in Panel A). Considering the current cash flow, medium firms are more sensitive to shortfalls, and their withdrawal credit lines are above average. Given the coefficient of interaction (*EBITDA* × *2020:Q2*), medium firms also present the most propensity of credit line drawdown in the pandemic shock, except for the contemporaneous cash flow (small firms desire larger size of drawdowns).

Table 3.8. **Cash Flow on Drawdowns by Firm Size**

This table presents the results of fixed-effect panel regressions of drawdowns by firm sizes. The dependent variables are drawdown size (columns (1) - (4)) and credit line usage (columns (5) - (8)), in which the drawdown size is the drawn amount of credit lines scaled by non-cash assets (where non-cash assets are equal to total assets less cash and cash equivalent) and the credit line usage is the drawn amount divided by the total amount of credit lines. Columns (1) and (5) examine the entire sample. The rest of the columns examine subsamples of firms, in which various firm sizes are selected and then aggregated to the whole level. The independent variables are EBITDA, the earnings before interest, taxes, depreciation, and amortization scaled by non-cash assets; 2020:Q2, a dummy variable that equals one indicating the time when the postponing effect of the pandemic happens. Controls include undrawn size, the undrawn amount of credit lines scaled by non-cash assets; tangibility, the tangible scaled by non-cash assets; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets; leverage ratio, the total debt divided by total assets. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Drawdown Size				Credit Line Usage			
	(1) All Firms	(2) Small Firms	(3) Medium Firms	(4) Large Firms	(5) All Firms	(6) Small Firms	(7) Medium Firms	(8) Large Firms
Panel A: Lagged Specification								
EBITDA_{t-1}	-0.559***	-0.249	-0.673**	-0.902**	-1.557**	-2.097	-1.564	-1.671
	(0.199)	(0.419)	(0.289)	(0.425)	(0.676)	(1.347)	(0.961)	(1.589)
EBITDA_{t-1}	-1.097*	-0.704	-3.274**	-2.790*	-5.071**	-0.997	-13.666***	-6.652
$\times$2020:Q2	(0.618)	(0.817)	(1.466)	(1.444)	(2.092)	(2.616)	(4.852)	(5.393)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	384	123	163	98	376	119	159	98
Adjusted R^2	0.021	0.038	0.062	0.178	0.036	0.075	0.149	0.047
OLS coefficient on	-0.634***	-0.395	-0.717**	-1.043**	-1.906***	-2.306*	-1.746*	-2.006
Cash Flow_{t-1}	(0.195)	(0.383)	(0.293)	(0.426)	(0.664)	(1.226)	(0.982)	(1.570)
Panel B: Contemporaneous Specification								
EBITDA_t	-0.327***	-0.098	-0.701**	-0.288	-1.127***	-0.679	-1.862**	-0.710
	(0.121)	(0.179)	(0.272)	(0.220)	(0.348)	(0.498)	(0.724)	(0.942)
EBITDA_t	-1.580***	-1.980**	-1.543**	0.479	-3.060**	-2.932	-3.812*	3.553
$\times$2020:Q2	(0.445)	(0.940)	(0.760)	(0.573)	(1.210)	(2.370)	(2.016)	(2.446)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	774	258	321	195	760	251	317	192
Adjusted R^2	0.175	0.190	0.152	0.083	0.057	0.070	0.055	0.018
OLS coefficient on	-0.424***	-0.156	-0.866***	-0.211	-1.343***	-0.791	-2.273***	-0.138
Cash Flow_t	(0.119)	(0.178)	(0.261)	(0.200)	(0.339)	(0.491)	(0.694)	(0.858)

3.5.2 Drawdowns on Cash Holdings by Firm Sizes

In this section, we examine whether the precautionary saving purpose still holds for different sizes of firms. We apply the specification of equation (3.4) for small, medium, and large firms and fix time effects. Columns (1) - (4) of Table 3.9 show the results. The coefficients of the term *Drawdown* describe that precautionary saving exists among all firms. Particularly, medium firms raise more cash from drawdowns than the rest (column (3) in Panel A). However, the coefficients in Panel B do not show significant results, which might support that the behaviour of drawdowns is for future savings. It is noticeable that the coefficients of the interaction term *Drawdown* $\times$ *2020:Q2* are insignificant, suggesting that the pandemic shock may have no remarkable effect on raising cash from credit lines.

Next, we consider the endogeneity and still use *Undrawn Capacity* as an instrument. Columns (5) - (8) in Table 3.9 show the results. Medium firms raise significantly more cash from credit line drawdowns than mean level (columns (5) & (7) in Panel A). Unexpectedly, large and small firms do not gain cash from withdrawing credit lines. This case is also supported by analysing the contemporaneous effect of drawdowns (Panel B). The pandemic shock still has no significant effect, except for medium firms (column (7) in Panel A).

3.5.3 Drawdowns on Investment by Firm Sizes

We again investigate investment behaviour in different subsamples of firm sizes, using the specification of equation (3.5). Firstly, we examine the OLS regression on the specification. Columns (1) - (4) in Table 3.10 show the effect of drawdowns on investment in all small, medium, and large firms. The coefficients of the term *Drawdown* suggest that corporate drawdowns are not for maintaining investment purposes, except for small firms (column (1) in Panel A). Besides, large firms have a greater negative effect of previous drawdowns than the rest (column (4) in Panel A), while current drawdowns have a greater effect on medium firms (column (3) in Panel B). The coefficients of the interaction (*Drawdown* $\times$ *2020:Q2*) are insignificant for all types of firms, which seems that the pandemic shock has no significant impact on investment.

Following the manner in section 3.4.2 on the endogeneity problem of investment, we set *Undrawn Capacity* as instrumental variable[14]. Columns (5) - (8) in Table 3.10 depicts the result of the IV regression. In line with the coefficient of the term *Drawdown*,

[14] *Undrawn Capacity* has an expression as *Undrawn Credit Line*/(*Undrawn Credit Line* + *Cash Holdings*). It measures the ability of unused credit lines as external liquidity.

Table 3.9. **Drawdowns on Cash Holdings by Firm Size**

This table presents the results of fixed-effect panel regressions of cash holdings by firm size. The dependent variables across all columns are cash holdings, measured by the cash and cash equivalent scaled by non-cash assets. In columns (1) to (4), the estimates are based on the OLS regression. In columns (5) to (8), the estimates are based on the IV regression, in which the instrument is undrawn capacity. Columns (1) and (5) examine the entire sample. The rest of the columns examine subsamples of firms, in which various firm sizes are selected and then aggregated to the whole level. The independent variables and the controls are the same as the ones in Table 3.8. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Firms	Small Firms	Medium Firms	Large Firms	All Firms	Small Firms	Medium Firms	Large Firms
Panel A: Lagged Specification								
Drawdown_{t-1}	0.131***	0.059	0.167***	-0.051	0.370**	-0.374	0.595***	-0.321**
	(0.045)	(0.107)	(0.049)	(0.115)	(0.161)	(1.099)	(0.196)	(0.157)
$\text{Drawdown}_{t-1}\times$2020:Q2	0.011	0.377	-0.270	0.228	-0.221	0.792	-0.656**	0.466
	(0.153)	(0.292)	(0.192)	(0.277)	(0.226)	(1.071)	(0.289)	(0.299)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	391	124	167	100	302	94	126	82
Adjusted R^2	0.373	0.427	0.485	0.188	0.270	0.362	0.283	0.023
Panel B: Contemporaneous Specification								
Drawdown_t	-0.006	0.032	0.031	0.040	0.285***	-0.022	0.423***	-0.244
	(0.036)	(0.071)	(0.039)	(0.084)	(0.106)	(0.272)	(0.131)	(0.147)
$\text{Drawdown}_t\times$2020:Q2	-0.047	-0.174	0.129	0.175	-0.140	-0.045	-0.249	0.387
	(0.094)	(0.183)	(0.100)	(0.236)	(0.139)	(0.339)	(0.156)	(0.285)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	816	277	335	204	375	119	157	99
Adjusted R^2	0.408	0.481	0.423	0.178	0.346	0.441	0.462	0.009

medium firms present a greater negative effect of drawdowns on investment than the average level (column (5) & (7)). Regarding the interaction term *Drawdown*$\times$ *2020:Q2*, previous drawdowns have a trivial effect on investment in the pandemic shock, while current drawdowns increase the investment on average. Medium firms, meanwhile, raise more cash for investment than average.

Table 3.10. **Drawdowns on Investment by Firm Size**

This table presents the results of fixed-effect panel regressions of investment by firm size. The dependent variables across all columns are investments, measured by the capital expenditure scaled by non-cash assets. In columns (1) to (4), the estimates are based on the OLS regression. In columns (5) to (8), the estimates are based on the IV regression, in which the instrument is undrawn capacity. Columns (1) and (5) examine the entire sample. The rest of the columns examine subsamples of firms, in which various firm sizes are selected and then aggregated to the whole level. The independent variables and the controls are the same as the ones in Table 3.8. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS				IV			
	(1) All Firms	(2) Small Firms	(3) Medium Firms	(4) Large Firms	(5) All Firms	(6) Small Firms	(7) Medium Firms	(8) Large Firms
Panel A: Lagged Specification								
Drawdown_{t-1}	-0.014**	0.008	-0.012	-0.022**	-0.043**	-0.104	-0.053*	-0.012
	(0.006)	(0.018)	(0.008)	(0.011)	(0.018)	(0.168)	(0.030)	(0.014)
$\text{Drawdown}_{t-1}\times$2020:Q2	-0.000	-0.016	-0.012	0.027	0.028	0.083	0.026	0.019
	(0.022)	(0.048)	(0.030)	(0.026)	(0.026)	(0.162)	(0.044)	(0.026)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	366	110	156	100	284	84	118	82
Adjusted R^2	0.099	0.089	0.078	0.227	0.051	-0.503	-0.107	0.144
Panel B: Contemporaneous Specification								
Drawdown_t	-0.015***	-0.011	-0.018***	-0.013	-0.042***	-0.049	-0.065***	-0.016
	(0.004)	(0.008)	(0.006)	(0.011)	(0.013)	(0.037)	(0.024)	(0.013)
$\text{Drawdown}_t\times$2020:Q2	0.004	0.003	0.005	0.020	0.029*	0.044	0.048*	0.024
	(0.011)	(0.021)	(0.014)	(0.031)	(0.017)	(0.044)	(0.028)	(0.025)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	707	229	298	180	354	107	148	99
Adjusted R^2	0.113	0.075	0.133	0.199	0.024	-0.051	-0.250	0.248

3.5.4 The Effect of Exposure: Individual SectorS

Next, we extend the analysis into each sector to investigate the effect of firm sizes on the industrial level. We construct a panel regression as follows:

$$Y_i \;=\; \alpha + \sum \beta_1(\mathit{Sectors}_i \times \mathit{2020{:}Q2}) + \tau_i + \gamma X_i + \epsilon_i \tag{3.7}$$

where Y_i still represents three dependent variables: Credit line usage, capital expenditure scaled by non-cash assets, and cash and cash equivalent scaled by the non-cash assets. $\mathit{Sectors}_i$ is an indicator for each level-1 BICS sector, such as Communications, Consumer Discretionary, Consumer Staples, Energy, Health Care, Industrials, Materials, Real Estate, Technology, and Utilities. The sector, Utilities, is set up as the base. *2020:Q2* is a dummy variable equal to 1 that the pandemic shock bursts. τ_i represents different firm sizes as in the previous section. X_i are a brunch of controls, including the undrawn credit lines relative to non-cash assets, the logarithm of non-cash assets, the price-to-book ratio, the percentage of the tangible assets to non-cash assets, and the leverage ratio. Results are reported in Table 3.11.

Regarding credit line usage, different sectors demonstrate remarkable heterogeneity. Although most of the coefficients of sectors in column (1) of Table 3.11 are insignificant, we can still find that sectors increase their usage during the pandemic shock, particularly the Energy sector increases its usage by 25.4%, significantly. Within the range of small firms in column (2), Real Estate has a salient increment of 74.3%. However, medium-sized firms in column (3), especially Communications, Consumer Discretionary, Industrials, Materials, and Technology, significantly reduce their credit line usage by around 50%. Large firms in column (4) are somewhat complicated in that Communications, Consumer Staples, and Industrials significantly increase credit line usage, while Real Estate decreases its drawdowns by 28.2%.

The heterogeneity of credit line usage also exists among different firm sizes. For instance, both Communications and Industrials sectors decrease their credit line usage by over 60% within the range of medium-sized firms. On the contrary, the large firms increase by around 25%. On the contrary, Real Estate has an increase of 74.3% in credit line usage among small-sized firms but a 28.2% decrease among large firms.

When it turns to investment, there may be little evidence to prove the reduction of capital expenditure, but the coefficients in column (5) of Table 3.11 can, to some extent, tell that most firms do not increase their investment when the pandemic shock happens. In columns (6) and (8), this situation continues. Small- and large-sized firms may reduce their investment during the pandemic. Sectors, such as Industrials, Materials, and Technology, significantly shrink their size of capital expenditure. Inversely, column

(7) indicates that some medium-sized firms from the Communications and Materials sectors increased their investment, proving the heterogeneity among industries and sizes. Taking Materials as an example, although medium-sized firms increase their investment during the shock, the large-sized ones still choose to reduce the size.

Cash holding is one of our concentrations because it can tell whether firms draw down their credit lines for precautionary savings. The salient heterogeneity in firm sizes and sectors also appears in cash holding in columns (9) - (12) of Table 3.11. Overall, the coefficients are insignificant in column (9), except the coefficients of Real Estate (-0.083) and Technology (0.079). Within the small-sized firms (column (10)), almost all sectors have negative signs, especially Health Care and Real Estate have significant ones. The same situation is inherited by medium-sized firms (column (11)), whereas half of the coefficients are salient. Large-sized firms, however, increase their cash holdings, especially the sectors of Consumer Discretionary, Health Care, Industrials, and Technology, which have significantly positive coefficients. As for the individual industry, medium-sized firms in Consumer Discretionary decrease their cash holdings, while large-sized ones increase. Small-sized firms in Health Care also reduce their cash, but large-sized firms, inversely, enhance the cash level. Some sectors, such as Real Estate and Technology, have homogeneous behaviours among different sizes of firms. Real Estate reduces their cash holdings, but Technology chooses to increase. In conclusion, large-sized firms prefer to hoard their cash for precautions, compared with small- and medium-sized ones.

Table 3.11. **Individually Industrial Exposure to COVID-19**

This table presents the results of fixed-effect panel regressions of individual industrial sectors. In columns (1) to (4), the dependent variables are the credit line usage, the drawdowns in proportion to total credit lines. In columns (5) to (8), the dependent variables are the investment, measured by the capital expenditure scaled by non-cash assets. In columns (9) to (12), the dependent variables are the cash holdings, the cash and cash equivalent scaled by non-cash assets. Columns (1), (5), and (9) examine the entire sample. The rest of the columns examine subsamples of sectors, in which various firm sizes are selected and then aggregated to the sector level. The independent variables are the interaction of the sector indicators and 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Control variables include undrawn credit lines, the logarithm of non-cash assets, the logarithm of price-to-book ratio, tangible assets, and leverage ratio. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Credit Line Usage				Investment				Cash Holdings			
	(1) All	(2) Small	(3) Medium	(4) Large	(5) All	(6) Small	(7) Medium	(8) Large	(9) All	(10) Small	(11) Medium	(12) Large
Communications×2020:Q2	-0.013		-0.642***	0.241**	0.003		0.010*	-0.002	0.050		-0.067*	0.052
	(0.111)		(0.241)	(0.115)	(0.005)		(0.006)	(0.006)	(0.033)		(0.037)	(0.032)
Consumer Discretionary×2020:Q2	0.027	-0.109	-0.428*	0.039	-0.005	-0.006	0.001	-0.003	0.037	0.027	-0.081***	0.046*
	(0.083)	(0.153)	(0.225)	(0.091)	(0.003)	(0.007)	(0.005)	(0.003)	(0.024)	(0.058)	(0.029)	(0.026)
Consumer Staples×2020:Q2	0.049	-0.133		0.438**	-0.003	0.000	0.001	-0.003	-0.020	-0.084	-0.188***	0.009
	(0.162)	(0.218)		(0.192)	(0.005)	(0.009)	(0.010)	(0.006)	(0.037)	(0.064)	(0.059)	(0.054)
Energy×2020:Q2	0.254*	0.311	0.189	-0.117	-0.000	-0.005	0.004	0.009	-0.011	-0.056	-0.072	-0.024
	(0.142)	(0.224)	(0.323)	(0.192)	(0.006)	(0.013)	(0.010)	(0.006)	(0.045)	(0.088)	(0.058)	(0.055)
Health Care×2020:Q2	0.029	-0.183	-0.292	0.136	-0.001	0.006	-0.001	-0.003	0.041	-0.166**	-0.035	0.128***
	(0.111)	(0.296)	(0.259)	(0.103)	(0.004)	(0.009)	(0.006)	(0.005)	(0.029)	(0.072)	(0.034)	(0.028)
Industrials×2020:Q2	0.009	-0.073	-0.612***	0.275***	-0.003	-0.002	0.004	-0.006**	0.031	-0.053	-0.039	0.067***
	(0.073)	(0.133)	(0.215)	(0.080)	(0.002)	(0.005)	(0.005)	(0.002)	(0.019)	(0.041)	(0.027)	(0.020)
Materials×2020:Q2	0.047	-0.085	-0.488**	0.008	-0.001	-0.003	0.009*	-0.005*	-0.009	-0.092	-0.063**	0.028
	(0.087)	(0.187)	(0.221)	(0.102)	(0.003)	(0.008)	(0.005)	(0.003)	(0.024)	(0.073)	(0.028)	(0.024)
Real Estate×2020:Q2	0.194	0.743**	-0.284	-0.282**	-0.003	0.000	-0.001	0.007	-0.083**	-0.222*	-0.135***	-0.034
	(0.129)	(0.298)	(0.270)	(0.140)	(0.005)	(.)	(0.006)	(0.006)	(0.035)	(0.120)	(0.035)	(0.039)
Technology×2020:Q2	0.020	0.174	-0.665**	-0.077	-0.004	-0.002	0.005	-0.008*	0.079***	-0.022	0.024	0.200***
	(0.102)	(0.145)	(0.320)	(0.138)	(0.004)	(0.007)	(0.009)	(0.004)	(0.029)	(0.051)	(0.043)	(0.039)
Constant	0.585***	0.331	0.185	1.249***	-0.000	0.008	-0.076***	-0.010	0.128***	0.023	0.649***	0.085
	(0.144)	(0.418)	(0.784)	(0.359)	(0.005)	(0.016)	(0.027)	(0.011)	(0.038)	(0.135)	(0.144)	(0.084)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	800	265	238	297	917	301	296	320	1100	378	357	365
Adjusted R^2	0.024	0.106	0.173	0.350	0.117	0.208	0.251	0.228	0.433	0.483	0.545	0.451

3.6 Corporate Credit Lines during the European Crisis

Is the precautionary purpose unique to the COVID-19 shock? To understand this issue, we construct a database covering the European crisis (2009:Q4 - 2013:Q4). We want to see whether firms also drew down credit lines for precautionary savings at the peak of the European Crisis shock when the Outright Monetary Transaction (OMT) was launched in the third quarter of 2012.[15] The empirical results in this section are not just an alternative robustness check of the previous sections but also an attempt to show the uniqueness of the COVID-19 shock to firms. In addition, it provides us insight into different shocks affecting corporate liquidity management.

3.6.1 Stylized Facts about Drawdowns during the European Crisis

Panel A of Figure 3.12 shows the average drawdown size (drawdowns scaled by non-cash assets). A three-quarter increase happened from 2012:Q2 to Q4, especially a sharp rise within the fourth quarter of 2012. Panel B of Figure 3.12 shows a similar trend by credit line usage (drawdowns scaled by total credit lines).

In the same period (2012:Q2 - Q4), Panel A of Figure 3.13 shows a different trend of cash holdings (cash and cash equivalents scaled by non-cash assets). Instead of a continuous increase like credit line drawdowns in Figure 3.12, cash holdings only increased in the third quarter of 2012. Meanwhile, Panel B of Figure 3.13 reports the investment size (capital expenditure scaled by non-cash assets). It presents merely a decrease in investment within the third quarter of 2012.

Table 3.12 provides summary statistics. The sampling period covers 17 quarters from 2009:Q4 to 2013:Q4. Intuitively, both drawdown size and credit line usage (0.046 and 0.141, respectively) during the European Crisis had similar values to those in the COVID-19 period (0.051 and 0.207, respectively). Particularly, the demand for credit lines was smaller during the European Crisis than during the pandemic. As for cash holdings, the value was 0.155 during the European Crisis, higher than that of the COVID-19 shock (0.107). Investments in both periods (0.011 in the European Crisis and 0.012 in the pandemic crisis) were almost identical.

[15]OMT is the potentially unlimited purchase of euro area sovereign bonds on the secondary market by the European Central Bank. The ECB President Mario Draghi announced the OMT in September 2012. Its purpose was to "safeguard an appropriate monetary policy transmission and the singleness of the monetary policy" to maintain the integrity of the euro area.

Panel A Panel B

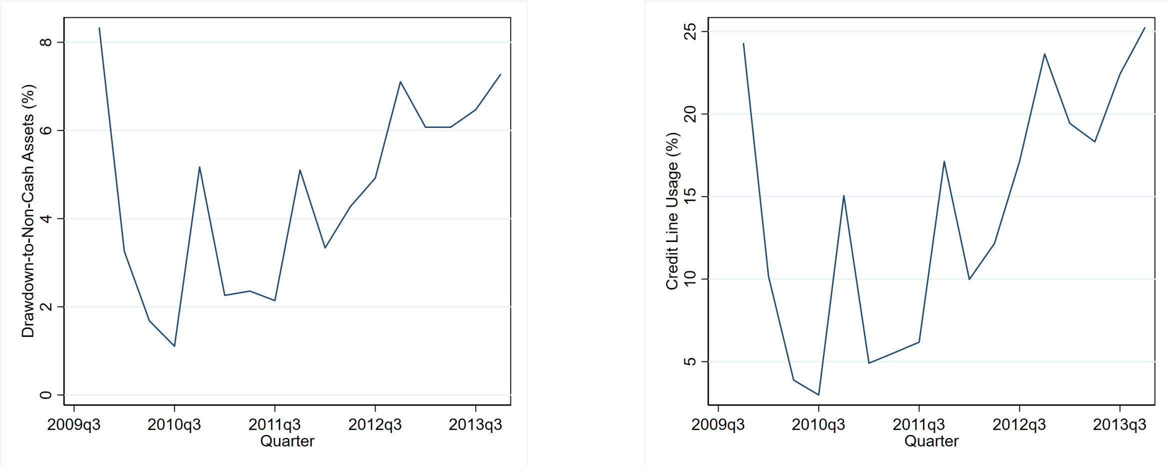

Figure 3.12. Credit Line Drawdown Size and Usage during European Crisis.

This figure plots the average credit line drawdowns and usage during the European crisis period (2009:Q4 - 2013:Q4). Panel A shows the drawdowns scaled by non-cash assets, while Panel B shows the credit line usage.

Panel A Panel B

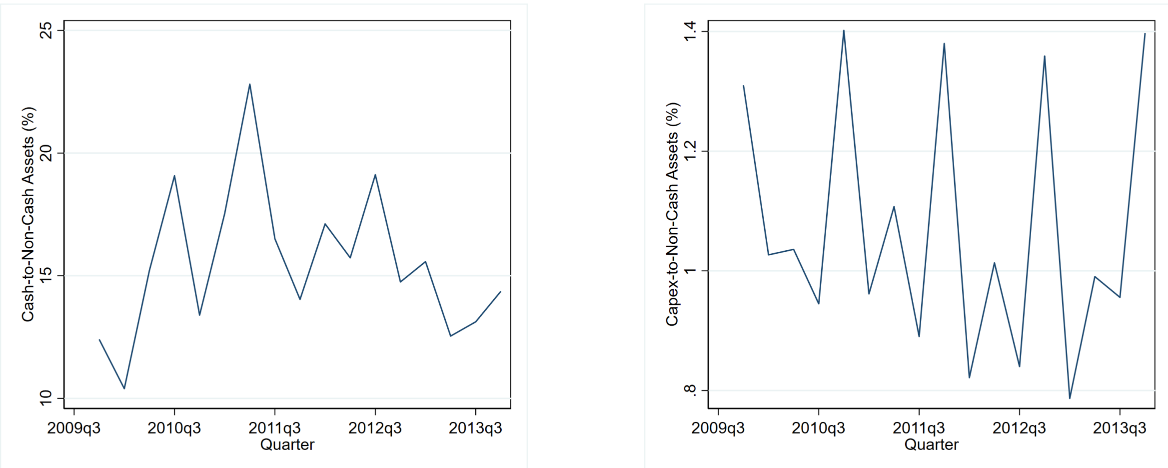

Figure 3.13. Cash Holdings and Investment during European Crisis.

This figure plots the average cash holdings and investment during the European crisis period (2009:Q4 - 2013:Q4). Panel A shows cash and cash equivalents scaled by non-cash assets, while Panel B shows the capital expenditure scaled by non-cash assets.

Table 3.12. **Summary Statistics of Regression Variables**
This table presents a description of the sample. The observations are collected from all Euro-area countries. The sampling period is from 2009:Q4 to 2013:Q4. All variables are winsorized at 5%. Appendix 3A contains all variable definitions.

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Drawdown Size	3,746	0.046	0.127	0.000	0.000	0.000	0.012	0.754
Credit Line Usage	3,766	0.141	0.271	0.000	0.000	0.000	0.127	1.000
Cash Holdings	5,105	0.155	0.378	0.000	0.026	0.060	0.145	4.024
CAPEX	3,511	0.011	0.015	0.000	0.002	0.007	0.015	0.114
Undrawn CL	5,105	0.083	0.117	0.000	0.000	0.041	0.123	0.782
log(P/B)	4,788	0.328	0.973	-2.408	-0.248	0.341	0.970	3.128
log(Assets)	5,105	19.156	2.664	12.663	17.366	19.055	21.123	25.476
Tangible Assets	4,779	0.897	0.384	0.126	0.697	0.925	1.023	4.002
Leverage	4,814	0.250	0.195	0.000	0.093	0.231	0.371	1.061

3.6.2 Does Precautionary Saving Purpose Hold for the European Crisis?

To test whether firms drew down credit lines for precautionary purposes during the European Crisis, we run the following fixed-effect panel regressions:

$$Y_{i,t} \quad = \quad \alpha + \beta_1 Drawdowns_{i,t} + \beta_2 Drawdowns_{i,t} \times \mathit{2012{:}Q3} + \gamma X_{i,t} + \epsilon_{i,t} \qquad (3.8)$$

where $Y_{i,t}$ contains two dependent variables: 1) *Cash Holdings*, measured by cash and cash equivalents scaled by non-cash assets, and 2) *Investment*, measured by capital expenditure scaled by non-cash assets. $Drawdowns_{i,t}$ is the independent variable also measured in two ways: 1) *Drawdown Size*, the credit line drawdowns divided by non-cash assets, and 2) *Credit Line Usage*, the drawn amount divided by the total amount of credit lines. *2012:Q3* is a time dummy indicating the launch of the OMT (the peak of the European Crisis). $X_{i,t}$ includes a set of controls such as the undrawn amount of credit lines, the logarithm of the price-to-book ratio, the logarithm of non-cash assets, tangible assets, and the leverage ratio. Time and industry-fixed effects are included. Appendix 3A contains all definitions of variables.

Did firms draw down For saving purpose during European Crisis?

First, we use firms' cash holdings as the dependent variable. Table 3.13 reports the results of the fixed-effect panel regression, with three dummies for each quarter from 2012:Q2 to Q4. Panel B of Table 3.13 using 2012:Q3 as a time dummy is our primary interest, while Panels A and C provide additional checks by using 2012:Q2 and

2012:Q4, respectively. Columns 1 & 2 show the OLS specification. Over the full sample period, we find that firms draw down credit lines for cash savings. A positive and significant coefficient on *Drawdown Size* shows evidence (column 1). When we include the interaction term, we find that the specific period has an insignificant contribution to the results. Firms did not withdraw credit lines to enrich their cash holdings in a short period.

As discussed, unused credit lines and cash holdings from the previous period are important instruments for assessing whether corporate drawdowns are endogenous to cash holdings. Columns 3 to 6 in Table 3.13 show the result of the IV specification. We find little or weak evidence that the endogenous problem exists in explaining firms' drawing down credit lines for precautionary purposes. In addition, we report the result of the lagged specification of the fixed-effect panel regression in Table 3.14, providing similar results as in Table 3.13.

Did firms use credit lines for investment during European Crisis?

Next, we run the fixed-effect panel regressions by using investment as the dependent variable. Table 3.15 shows the results. Similarly, Panel B of Table 3.15 is our main focus, while Panels A & C provide alternative tests. We run the OLS regression in columns 1 and 2. The significant and negative coefficient on *Drawdown Size* suggests that firms drawing down credit facilities were not for investment purposes in the European Crisis. The coefficients on the interaction terms across Panels A to C are insignificant. The shock from the launch of the OMT had little effect on firms' investment decisions via credit lines.

We also include undrawn credit lines and cash holdings in the previous period as instruments to investigate whether the endogenous problem exists in firms' credit line utilization for investment. Columns 3 - 6 in Table 3.15 report the results of the IV regression. Given credit line drawdowns conditional on undrawn credit lines (columns 3 and 4), we find significant and negative coefficients on *Drawdown Size* over the full sample. However, the coefficients on the interaction terms with different time dummies are insignificant. It suggests that the specific shock period did not significantly contribute to firms' investment decisions during the European Crisis.

We use lagged independent and control variables as an alternative test for the fixed-effect panel regression. Table 3.16 reports the results of the lagged specification. The results are mostly insignificant, providing little evidence that firms withdrew credit lines for investment during the European Crisis.

Table 3.13. **Cash Holdings and Drawdowns**

This table presents the results of panel regression of firms' cash holdings. The dependent variables across all columns are the cash holding size equal to cash and cash equivalent scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are drawdown size, the drawn amount of credit lines scaled by non-cash assets; 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2012:Q2						
Drawdown Size$_t$	0.064**	0.064**	0.132*	0.134*	-2.384	-2.379
	(0.031)	(0.031)	(0.076)	(0.078)	(5.110)	(5.111)
Drawdown Size$_t$×2012:Q2		0.052		-0.031		0.161
		(0.209)		(0.233)		(0.288)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	3116	3116	1513	1513	2151	2151
Adjusted R^2	0.737	0.737	0.748	0.748	0.703	0.703
Panel B: 2012:Q3						
Drawdown Size$_t$	0.064**	0.065**	0.132*	0.122	-2.384	-2.391
	(0.031)	(0.031)	(0.076)	(0.077)	(5.110)	(5.111)
Drawdown Size$_t$×2012:Q3		-0.042		0.190		-0.176
		(0.205)		(0.260)		(0.309)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	3116	3116	1513	1513	2151	2151
Adjusted R^2	0.737	0.737	0.748	0.748	0.703	0.703
Panel C: 2012:Q4						
Drawdown Size$_t$	0.064**	0.056*	0.132*	0.120	-2.384	-2.369
	(0.031)	(0.033)	(0.076)	(0.078)	(5.110)	(5.111)
Drawdown Size$_t$×2012:Q4		0.058		0.141		0.167
		(0.082)		(0.201)		(0.241)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	3116	3116	1513	1513	2151	2151
Adjusted R^2	0.737	0.737	0.748	0.748	0.703	0.703

Table 3.14. **Cash Holdings and Drawdowns (Lagged Specification)**
This table presents the results of panel regression of firms' cash holdings on credit line drawdowns. The dependent variables across all columns are cash and cash equivalent scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are *Drawdown Size*, the drawn amount of credit lines scaled by non-cash assets; *2020:Q2*, a time dummy indicating the second quarter of 2012. *2020:Q3*, a time dummy indicating the third quarter of 2012. *2020:Q4*, a time dummy indicating the fourth quarter of 2012. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; the logarithm of price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Appendix 3A contains all variable definitions. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2012:Q2						
Drawdown Size$_{t-1}$	0.054	0.065	0.175*	0.187*	-29.099	-29.131
	(0.052)	(0.054)	(0.099)	(0.102)	(90.403)	(90.431)
Drawdown Size$_{t-1}$×2012:Q2		-0.176		-0.138		-0.079
		(0.200)		(0.286)		(0.363)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1512	1512	1083	1083	1612	1612
Adjusted R^2	0.628	0.628	0.661	0.661	0.617	0.617
Panel B: 2012:Q3						
Drawdown Size$_{t-1}$	0.054	0.054	0.175*	0.194*	-29.099	-29.254
	(0.052)	(0.053)	(0.099)	(0.102)	(90.403)	(90.416)
Drawdown Size$_{t-1}$×2012:Q3		-0.010		-0.237		-0.264
		(0.246)		(0.280)		(0.349)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1512	1512	1083	1083	1612	1612
Adjusted R^2	0.628	0.628	0.661	0.661	0.617	0.617
Panel C: 2012:Q4						
Drawdown Size$_{t-1}$	0.054	0.040	0.175*	0.143	-29.099	-28.669
	(0.052)	(0.053)	(0.099)	(0.101)	(90.403)	(90.395)
Drawdown Size$_{t-1}$×2012:Q4		0.392		0.523		0.423
		(0.242)		(0.321)		(0.366)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1512	1512	1083	1083	1612	1612
Adjusted R^2	0.628	0.629	0.661	0.662	0.617	0.617

Table 3.15. **Investment and Drawdowns**

This table presents the results of panel regression of firms' cash holdings. The dependent variables across all columns are the cash holding size equal to cash and cash equivalent scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are drawdown size, the drawn amount of credit lines scaled by non-cash assets; 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2012:Q2						
Drawdown Size$_t$	-0.008**	-0.007**	-0.018***	-0.018***	-0.361	-0.362
	(0.003)	(0.003)	(0.007)	(0.007)	(0.567)	(0.567)
Drawdown Size$_t$×2012:Q2		-0.010		0.011		-0.009
		(0.022)		(0.022)		(0.028)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	2301	2301	1145	1145	1535	1535
R^2	0.098	0.098	0.090	0.090	0.088	0.089
Panel B: 2012:Q3						
Drawdown Size$_t$	-0.008**	-0.007**	-0.018***	-0.018***	-0.361	-0.362
	(0.003)	(0.003)	(0.007)	(0.007)	(0.567)	(0.567)
Drawdown Size$_t$×2012:Q3		-0.009		0.000		-0.005
		(0.023)		(0.022)		(0.029)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	2301	2301	1145	1145	1535	1535
R^2	0.098	0.098	0.090	0.090	0.088	0.089
Panel C: 2012:Q4						
Drawdown Size$_t$	-0.008**	-0.008**	-0.018***	-0.017**	-0.361	-0.361
	(0.003)	(0.003)	(0.007)	(0.007)	(0.567)	(0.567)
Drawdown Size$_t$×2012:Q4		0.002		-0.007		0.008
		(0.008)		(0.018)		(0.024)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	2301	2301	1145	1145	1535	1535
R^2	0.098	0.098	0.090	0.090	0.088	0.089

Table 3.16. **Investment and Drawdowns (Lagged Specification)**

This table presents the results of panel regression of firms' cash holdings. The dependent variables across all columns are the cash holding size equal to cash and cash equivalent scaled by non-cash assets (where non-cash assets are total assets less cash and cash equivalent). The independent variables are drawdown size, the drawn amount of credit lines scaled by non-cash assets; 2020:Q2, a dummy equal to one that indicates the time when the postponing effect of the pandemic happens. Controls contain the undrawn size, the undrawn credit lines scaled by non-cash assets; tangibility, the tangible assets scaled by non-cash ones; price-to-book ratio, the stock price per share divided by the book value per share; the logarithm of non-cash assets, indicating the firm size; leverage ratio, the total debt divided by total assets. Columns (1) and (2) present the OLS estimation between cash holdings and drawdowns. Columns (3) to (6) present the endogenous estimations in which the instruments are undrawn capacity (the undrawn credit lines scaled by the sum of undrawn credit lines and cash and cash equivalent) and lagged cash holdings. Standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	OLS		IV			
			Undrawn Capacity		Cash Holdings	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2012:Q2						
Drawdown Size$_{t-1}$	-0.015***	-0.014***	-0.015**	-0.015**	4.657	4.658
	(0.004)	(0.004)	(0.006)	(0.006)	(6.905)	(6.908)
Drawdown Size$_{t-1}\times$2012:Q2		-0.016		0.008		0.003
		(0.020)		(0.018)		(0.028)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1140	1140	842	842	1171	1171
R^2	0.092	0.093	0.089	0.089	0.077	0.077
Panel B: 2012:Q3						
Drawdown Size$_{t-1}$	-0.015***	-0.015***	-0.015**	-0.015**	4.657	4.650
	(0.004)	(0.004)	(0.006)	(0.006)	(6.905)	(6.908)
Drawdown Size$_{t-1}\times$2012:Q3		-0.008		0.011		-0.006
		(0.019)		(0.020)		(0.029)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1140	1140	842	842	1171	1171
R^2	0.092	0.093	0.089	0.089	0.077	0.077
Panel C: 2012:Q4						
Drawdown Size$_{t-1}$	-0.015***	-0.014***	-0.015**	-0.014**	4.657	4.691
	(0.004)	(0.004)	(0.006)	(0.006)	(6.905)	(6.906)
Drawdown Size$_{t-1}\times$2012:Q4		-0.021		-0.011		0.022
		(0.020)		(0.020)		(0.028)
Controls	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
Observations	1140	1140	842	842	1171	1171
R^2	0.092	0.093	0.089	0.089	0.077	0.077

3.7 Conclusion

This paper sheds light on the use of credit lines by European firms during the COVID-19 crisis. We find that firms with higher short-term credit risk were more likely to draw down credit lines to alleviate cash flow shortfalls. This finding is consistent with previous research conducted in the US market during the pandemic and in the European market during the Global Financial Crisis. Our analysis reveals that firms predominantly accessed credit lines for precautionary purposes rather than for investment. Cash flow management and risk mitigation were key drivers behind credit line drawdowns. The relationship between credit line usage and investment was not significant, indicating that firms did not rely on credit lines to support investment activities during the COVID-19 crisis. Furthermore, we observe that medium-sized firms displayed a higher sensitivity to cash flow shortfalls, resulting in increased credit line withdrawals during the pandemic. These firms also held a larger proportion of cash through credit line drawdowns compared to other firm sizes. Our examination of the European Crisis highlights the unique nature of the COVID-19 crisis. Precautionary saving motives were not prevalent during the European Crisis, further distinguishing it from the COVID-19 crisis. The negative relationship between credit line drawdowns and investment observed during the pandemic provides additional evidence supporting our findings.

Future studies could expand on our research by exploring the dynamics of credit line usage in different industries, analyzing the impact of government policies and interventions on credit line utilization, and investigating the long-term effects of credit line drawdowns on firm performance and financial stability.

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Appendices

3A Description of Variables

Table 3A1. **Description of Variable**

Variable	Description	Source
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. Scaled by non-cash assets.	Bloomberg
CAPEX	CAPEX is the short name of capital expenditure. Amount the company spent on purchases of tangible fixed assets. Note that capital expenditure is taken its absolute value. Scaled by non-cash assets.	Bloomberg
Drawdown Size	Amount of the credit line that is currently used, equivalent to the total lines of credit less the undrawn credit lines. Scaled by non-cash assets.	Bloomberg
Credit Line Usage	The drawn amount of credit lines divided by the total committed amount.	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. Scaled by non-cash assets.	Bloomberg
Undrawn Capacity	The ratio is equal to 1 minus credit line usage, representing the remaining percentage of committed credit line.	Bloomberg
EBITDA	Net income with interest, taxes, depreciation, and amortization. EBITDA is commonly used as the measurement of cash flow by commercial banks to set various types of covenants on lines of credit. Scaled by non-cash assets.	Bloomberg
Log(P\B)	The natural logarithm of price-to-book ratio (P/B). P/B is the ratio of the stock price to the book value per share.	Bloomberg

(Continued on next page)

Table 3A1 – continued from previous page

Variable	**Description**	**Source**
Log(Assets)	The natural logarithm of non-cash assets. Non-cash assets is total assets, including the total of all short and long-term assets as reported on the Balance Sheet, less cash and cash equivalents.	Bloomberg
Tangible Assets	Total assets minus intangible assets. Scaled by non-cash assets.	Bloomberg
Leverage	The total amount of debt relative to assets.	Bloomberg
Credit Ratings	An indicator for each rating class based on S&P Issuer Rating, such as *AAA-A*, *BBB* or *Non-IG*.	Bloomberg
Rated	A dummy equal to one that a firm has a credit rating, and zero otherwise.	Bloomberg
AAA-A	A dummy equal to one that a firm has a credit rating of at least A-, and zero otherwise.	Bloomberg
BBB	A dummy equal to one that a firm has a credit rating of either BBB-, BBB, or BBB+, and zero otherwise.	Bloomberg
Non-IG	A dummy equal to one that a firm has a credit rating below BBB-, and zero otherwise.	Bloomberg
IG	A dummy equal to one that a firm has a credit rating of at least BBB-, and zero otherwise.	Bloomberg
Exposure at Default (EAD)	An index equal to $\textit{Drawdown Size} + \textit{CCF} \times \textit{Undrawn CL}$. CCF, or Credit Conversion Factor, is equal to $\frac{\textit{Drawdowns}-\textit{Previous Drawdowns}}{\textit{Previous Undrawn Credit Lines}}$.	Bloomberg
High Risk	A dummy equal to one that a firm has EAD at the top tertile (66.7% - 100%), and zero otherwise.	Bloomberg
Low Risk	A dummy equal to one that a firm has EAD at the bottom tertile (0% - 33.3%), and zero otherwise.	Bloomberg

3B Drawdowns and Committed Credit Lines

Table 3B1. **Drawn and Total Committed Credit Lines by Quarters (€Billion)**

Quarter	Firm Numbers	Drawn Credit Lines		Total Committed Credit Lines	
		Total Amount	Weighted Average	Total Amount	Weighted Average
2018:Q4	286	39.378	0.138	279.465	0.977
2019:Q1	80	8.506	0.106	63.689	0.796
2019:Q2	122	11.418	0.094	106.027	0.869
2019:Q3	87	9.504	0.109	71.005	0.816
2019:Q4	272	46.4	0.171	327.686	1.205
2020:Q1	85	17.63	0.207	84.012	0.988
2020:Q2	128	25.529	0.199	125.033	0.977
2020:Q3	99	26.508	0.268	89.411	0.903

Chapter 4

Firm-Oriented Credit Line Model

Abstract

Literature focuses on lenders' determinants in credit line issuance, but little work mentions why borrowers choose this debt financing tool. We develop a corporate financing and investment model and explore the optimal operation decision for demanding credit lines. Our model highlights the solvency risk in firms' credit line usage and provides rationales for firms drawing credit lines for cash savings in aggregate shocks. Using European data during the COVID-19 crisis, we provide stylized facts about credit line usage, pandemic exposure, and corporate productivity.
Keywords: Cash, Credit lines, Solvency risk, Investment
Classification codes: G31, G32

4.1 Introduction

Over the past decade, corporate credit lines become an essential financing tool within the Euro Area. Using credit line information of firms in the Euro Area, Figure 4.1 shows that lines of credit accounted for around 15% of a firm's total assets, and the drawdowns accounted for nearly 5%, providing them with an active channel to raise financing for several purposes. It is also supported by Lins et al. (2010)'s survey evidence. Although empirical and theoretical papers highlight the determinants of lenders (i.e. banks) in channelling credits, little work concentrates on the factor of borrowers (i.e. firms) demanding credit lines.

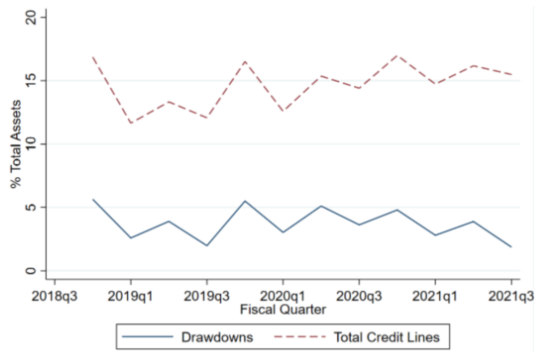


Figure 4.1. Drawdown and Total Credit Lines.

This figure plots the quarterly average of credit line drawdowns and total credit lines of European firms during 2018:Q4 - 2021:Q3.

In this paper, we propose a general model of firm value generation based on two determinants. First, a firm has internal funds from shareholders' investments and raises external funds by drawing down banks' credit lines. Second, the firm hoards some of its overall funds into its bank account and invests the rest into risky assets. This model aims to find the optimal capital structure and investment decision and the implication for the demand in credit lines.

We use a calibrated representative firm to show the benefit of credit lines in wealth generation. If a firm channels 75% of funds to risky assets, its worth would increase by 13% when it increases credit line usage from 21% to 71%. However, the overuse of credit lines (for example, furthering the utilization to 100%) could bring a 2% decrease in firm worth. In this way, the credit line is more than a substitute for cash holdings as in literature (e.g. Lins et al. (2010)).

A foundation of our analysis is the significance of capital structure. Theoretical papers focus on drawing credit lines to generate assets and buffer against liquidity shortfall (e.g. Boot et al. 1987, Holmström & Tirole 1998, Acharya, Almeida, Ippolito & Perez 2014*a*). Only a few mention the drawdown repayment (e.g. Nikolov et al. (2019), Cooperman et al. (2023)). We emphasize the role of corporate solvency in wealth maximization policy. The other important ingredient in our model is hoarding cash. In the COVID recession, credit line drawdowns were mainly for dashing for cash (Acharya & Steffen 2020*b*). In other words, firms kept a large part of drawdowns in bank accounts instead of funding investments. Although they incurred a high opportunity cost, the benefit of keeping cash seemed to be more attractive. Thus, we discuss the trade-off between holding cash and funding investment. In particular, by jointly considering these two items, our model predicts that the calibrated firm's net worth with respect to credit line usage would increase by 5.5% on average.

In Allen et al. (2015)'s financial intermediation model, they assume that banks finance their investment in a risky technology through deposit and equity. Their objective problem is to maximize the return on investment net of the deposit payment, as well as the opportunity cost for shareholders to provide capital. In this way, the investment decision would interact with the firm's debt repayment capacity and shareholders' equity value, which satisfies both creditors and shareholders.[1] We arbitrarily transfer banks' deposit payment problems to firms' debt repayment issues. Moreover, the firm can hedge the cost of capital by hoarding a part of the funds into its bank deposit account (Holmström & Tirole 1998, Acharya, Almeida, Ippolito & Perez 2014*a*).

Our analysis consists of three parts. First, we begin with a simple example: a firm finances itself with shareholders' equity and banks' credit lines and allocates all funds into riskless (i.e. cash holdings) and risky assets.[2] With a fixed equity capital and a certain line commitment, managers can decide the drawdown amount and the allocation of overall funds. By giving the firm the choice of credit line drawdowns without borrowing costs, we show that it can generate more worth through more aggressive investment and reduce the default risk by applying a more flexible liquidity management method.

In the second part, we construct a detailed baseline model considering the firm's productivity, risk-free return, and cost of borrowing. In this framework, the firm must tackle the trade-off between the benefit and the cost of using credit lines. Regarding the benefit, drawdowns can provide funds for profitable investment and holding undrawn lines can offer more flexible and efficient liquidity for future liquidity needs, as shown in Nikolov et al. (2019). However, both used and unused credit lines bring direct costs, such as the interest payment of drawdowns based on a loan rate and the commitment fee based on the undrawn amount (see Berg et al. (2016)). Thus, the framework describes the firm's internal operations in conjunction with external economic conditions. We show that in equilibrium, a firm can hoard more cash if the overall costs of credit lines

[1]Literature would simply treat deposits as a form of debt to banks (e.g. Diamond (1984)).

[2]Risky assets are far less liquid than cash holdings, so firms cannot transfer them immediately into liquidity when facing an income shortfall.

are too high or lower the drawn amount if the investment target is too high.

We then extend the model to several dimensions in which the calibrated representative firm should respond in different ways. To approach reality, we first allow the borrowing costs to vary, which makes the corporate profit move inversely against the cost. With a rise in the cost of borrowing, the firm is less likely to draw the undrawn balance when it sets an invariant investment level, supported by recent literature (see Cooperman et al. (2023)). If the firm fixes the level of credit line usage, it will seek high returns on risky assets to increase repayment. Although Lian et al. (2019) suggests that low loan rates lead to high investments in risky assets, we show a different finding that a lower borrowing cost encourages the firm to keep more cash holdings.

Next, we allow the firm to decide the amount of total committed credit lines (credit line drawdowns plus unused credit lines). Even though the firm has dominant bargaining power in contracting line commitments, the wealth maximization policy will not let the firm keep an infinitely large amount of commitments.[3] This implication highlights that any firms with revolving credit facilities should incur the direct costs from on-balance-sheet debt (i.e. the borrowing costs of credit line drawdowns) and off-balance-sheet items (i.e. the commitment fee of undrawn credit lines) when they channel external funds to investment. In this way, they need to balance off the wealth generation role and the cost of choosing credit lines.

To show the importance of the wealth maximization policy, we construct an alternative model of the asset maximization policy. If managers switch their targets from shareholders' equity generation to asset generation, the firm's profit will drop by 7%. The firm must face a conflict between overall assets and shareholders' wealth generation when it makes the investment decision.

Since the role of credit line drawdowns is funding investment, we explore the association of credit line usage with a firm's idiosyncratic productivity, especially in different market conditions. We show that when the economic environment is stable, high-yield firms (i.e. firms with relatively high productivity) have a higher ability to borrow from revolving credit facilities than low-yield firms (i.e. firms with relatively low productivity). These high-yield firms can benefit from the flexible options of drawn funds, while low-yield firms have very limited choices. When both types of firms suffer from a high-risk market circumstance, like the COVID-19 recession, they present similar behaviour patterns. As the aggregate risk elevates, they have irrational "panic borrowing" by drawing as many credit lines as possible. When the market starts to recover, they reduce credit line usage once they contract more line commitments.

[3] Our model implies that, for example, both contracting €0.2bn or €0.6bn committed lines cannot bring the utmost profit, but the amount of €0.4bn ones can.

The indirect costs of credit lines are the inflexibility due to banks' covenant restrictions. These restrictions, or covenant violations, are important instruments that banks monitor credit line contracts and even limit firms' drawdown behaviours (see Sufi (2009), Acharya, Almeida, Ippolito & Perez-Orive (2014), Chodorow-Reich & Falato (2022)). Including covenant violation into the corporate default risk, we have a novel finding that a firm's wealth is negatively related to its flexibility of accessing undrawn credit lines. In other words, the more strict the covenant, the higher the corporate profit.

In the third and final part of our analysis, we empirically evaluate the model's power to rationalize the utilization of revolving credit facilities. We use a uniform data source, Bloomberg, to collect the firm-level credit line and balance sheet data. We apply a mean of structural estimation named simulated method of moments (SMM). Our estimation results present that a 1% increase in risky assets leads to a 0.64% increment in production. To investigate the changes in firms' productivity during the COVID-19 pandemic, we create two sub-samples denoting before- and during-COVID periods, respectively, and find a 60.8% decline in corporate productivity during the pandemic. By dividing firm types based on the pandemic exposure, we explore how the labour factor affected corporate productivity during the pandemic-induced lockdown.

4.1.1 Related Literature

Our research lies at the crossroads of various literature strands. First, we draw from the expanding literature that employs theoretical models to provide a quantitative explanation for corporate investment and financing policies. Some early theoretical papers include Campbell (1978), Boot et al. (1987), Berkovitch & Greenbaum (1991), Duan & Yoon (1993), Holmström & Tirole (1998), Morgan (1994), and Thakor (2005). We contribute to this literature by explicitly considering liquidity management. As for recent theoretical papers, such as Acharya, Almeida, Ippolito & Perez (2014*a*), Nikolov et al. (2019), Greenwald et al. (2020), and Cooperman et al. (2023), they mainly discuss the lenders (i.e. banks) of credit lines. We shed some light on this paper and explore the credit line usage behaviours of the borrowers (i.e. firms).

In addition, our paper is closely related to the literature that focuses on the relationship between a credit line and capital structure, such as Shockley (1995), DeMarzo & Sannikov (2006), DeMarzo & Fishman (2007), and Biais et al. (2007). We differ from these models deriving credit line drawdowns and equity as optimal securities in a dynamic way. Our model explores capital structure optimization from a relatively static perspective (only two periods), providing a convenient extension method. For example, we can examine how the firm's profit changes in response to macroeconomic conditions (i.e. risk-free rate and shock term) and idiosyncratic productivity.

Another tight connection to the literature lies in the link between credit lines and corporate default risk. Only a few papers, including Mester et al. (2007), Jiménez et al. (2009), and Norden & Weber (2010), present empirical evidence of how borrowers' quality affects debt contracting and financial intermediation. We provide the theoretical framework to rationalize this process.

More generally, we contribute to public economics papers about the labour impacts of the COVID-19 pandemic. These papers, such as Dingel & Neiman (2020), Adams-Prassl et al. (2020), and Mongey et al. (2021), study the inequality of the pandemic exposure in industries. Our paper develops upon these studies and explores how this inequality affects firms' productivity. In addition, very few papers, like Campello et al. (2020), investigate the connection between the labour factor and credit line usage. Our work adds up to this kind of research.

This paper is organized as follows. Section 4.2 presents fundamental concepts by offering a brief overview of a company's life cycle. The primary concepts are introduced through a straightforward numerical example. This example shows the process of funding internal and external sources and investing in different assets. We develop this process into a detailed model of corporate investment, financing and liquidity management in Section 4.3. Section 4.4 extends the baseline model and includes the effect of loan rate and line commitments on credit line usage, followed by an alternative model to emphasize the wealth maximization policy in Section 4.5. We investigate the relationship between productivity, market risk, and credit line utilization in Section 4.6. Then, we explore the effect of covenant violation in firms' operations in Section 4.7. The structural estimation of the model's rationale comes in Section 4.8. Section 4.9 concludes.

4.2 An Example

As a brief introduction to our full model, we use simple examples to illustrate the main concepts and the economic trade-offs. The examples depict the life cycle of corporate operation and different scenarios of firm value generation. In particular, we illustrate how a firm uses credit lines to create more worth and avoid default risk. Overall, we show the relationship between endogenous liquidity management and the exogenous effect of cash flow shocks. For simplicity, we assume no risk-free return and interest payment.

4.2.1 Without Credit Lines

Consider a firm raising funds only from shareholders' investment at time $t = 0$. To generate shareholders' wealth, it must allocate its capital to risky assets or combinations of risky and risk-free assets. Clearly, only the investment in risky assets can provide high profit at time $t = 1$, but allocating partial funds to risk-free assets can contribute to hedging the risk from investment. More precisely, the firm confronts a good and a bad cash flow state at time $t = 1$. A one-dollar investment can obtain more than or equal to a one-dollar return in a good state. The opposite state provides less than one dollar return.

Initially, the shareholders' equity at time $t = 0$ is worth, say, $E_0 = 2.5$. Given the funds, the firm allocates them to risk-free assets (C_0) and risky assets (I_0). The allocations are $C_0 = 1$ and $I_0 = 1.5$. In a good state, the firm faces a life cycle as follows:

$t = 0$ $\qquad\qquad\qquad\qquad$ $t = 1$

$$\begin{tikzcd}
& C_0 = 1 \arrow[r] & C_1 = 1 \arrow[dr] & \\
E_0 = 2.5 \arrow[ur] \arrow[dr] & & & E_1 = 3 \\
& I_0 = 1.5 \arrow[r] & I_1 = 2 \arrow[ur] &
\end{tikzcd}$$

At time $t = 1$, the risk-free assets are still $C_1 = 1$, postulating the absence of risk-free return. The payoff of the risky investment is realized, equal to $I_1 = 2$. Eventually, the shareholders' equity expands to $E_1 = 3$. If the firm faces a negative cash flow shock (i.e., a bad state), its return on risky investment will not reach the original level, like $I_1 = 0.5$. Then, the shareholders' equity at time $t = 1$ shrinks, equal to $E_1 = 1.5$. The following figure depicts how the shareholders' wealth is harmed:

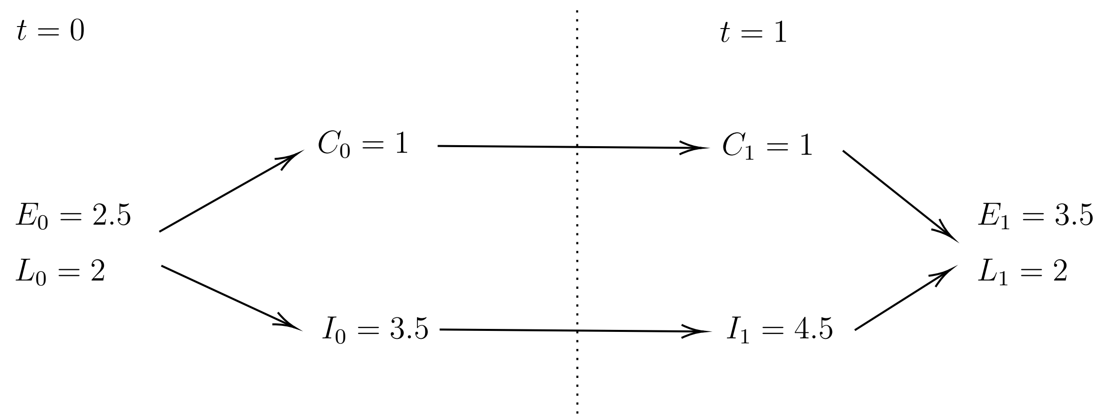
$t = 0$ $\qquad\qquad\qquad\qquad$ $t = 1$

$$\begin{tikzcd}
& C_0 = 1 \arrow[r] & C_1 = 1 \arrow[dr] & \\
E_0 = 2.5 \arrow[ur] \arrow[dr] & & & E_1 = 1.5 \\
& I_0 = 1.5 \arrow[r] & I_1 = 0.5 \arrow[ur] &
\end{tikzcd}$$

4.2.2 With Credit Lines

Suppose a firm can rely on banks' credit lines for external financing. Together with shareholders' investment, the firm can finance a larger scale of assets than only relying on internal funding. Similarly, it allocates all capital to risk-free and risky assets and anticipates good and bad states. When the return on risky investment is realized, the firm must repay the debt from external funding.

Let us denote the borrowing from credit lines, or credit line drawdowns, at time $t = 0$ as L_0 and the debt to repay at time $t = 1$ as L_1. In the beginning, the firm raises the same amount from shareholders, $E_0 = 2.5$, and credit lines from banks, say, $L_0 = 2$. Assuming both risk-free return and cost of borrowing are absent, the life cycle of corporate operation is shown as follows:



Given the overall capital of 4.5 ($E_0 + L_0$), the firm allocates it to risk-free assets of $C_0 = 1$ and risky assets of $I_0 = 3.5$ at time $t = 0$. In a good state at time $t = 1$, the risky investment provides $I_1 = 4.5$ as return, and the risk-free assets are still the same ($C_1 = 1$). After repaying the debt from credit line drawdowns as $L_1 = 2$, the remaining shareholders' equity becomes $E_1 = 3.5$. Compared with the previous section, the firm enjoys larger wealth ($E_1 = 3.5 > 3$) because the more funding, the more investment opportunities.

Nevertheless, it is, in the meantime, a trade-off of using credit lines since the firm also faces the default risk. In the bad state, once the risky investment cannot produce a sufficient return, it may threaten the firm's solvency. The following figure illustrates how the guarantee of repayment affects firm wealth:

At the time $t = 0$, the firm allocates the overall capital of $E_0 + L_0 = 4.5$ to risk-free and risky assets as $C_0 = 1$ and $I_0 = 3.5$, respectively. At time $t = 1$, the risk-free assets remain the same, while the risky assets yield a small amount of return, $I_1 = 0.5$. Considering the debt payment of $L_1 = 2$, the shareholders' equity even becomes negative, which is $E_1 = -0.5$. In reality, the equity value can only be non-

$$
\begin{tikzcd}
t=0 & & t=1 & \\
 & C_0 = 1 \arrow[r] & C_1 = 1 \arrow[dr] & \\
E_0 = 2.5 \arrow[ur] & & & E_1 = -0.5 \\
L_0 = 2 \arrow[dr] & & & L_1 = 2 \\
 & I_0 = 3.5 \arrow[r] & I_1 = 0.5 \arrow[ur] &
\end{tikzcd}
$$

negative. Thus, this example implies the firm's bankruptcy.

If the firm anticipates a relatively high default risk, it will lower the level of borrowing from banks' revolving credit facilities. Like the following figure, the firm draws down a smaller amount of credit lines than before:

$$
\begin{tikzcd}
t=0 & & t=1 & \\
 & C_0 = 1 \arrow[r] & C_1 = 1 \arrow[dr] & \\
E_0 = 2.5 \arrow[ur] & & & E_1 = 0.5 \\
L_0 = 1 \arrow[dr] & & & L_1 = 1 \\
 & I_0 = 2.5 \arrow[r] & I_1 = 0.5 \arrow[ur] &
\end{tikzcd}
$$

The drawdown size is equal to $L_0 = 1$ at time $t = 0$. To ensure the debt payment, the firm distributes the capital to safe assets of $C_0 = 1$, the same amount as credit line drawdowns. Although the risky investment of 2.5 yields merely 0.5 return at time $t = 1$, the shareholders' equity remains positive, which keeps the firm surviving from bankruptcy.

4.2.3 Equity, Credit Lines, and Assets

In this example, a firm finances its assets through only shareholders' investments or the combination of shareholders' equity and banks' credit lines. The firm may generate or lose wealth in good and bad states by allocating the overall capital to different assets.

Without credit lines, a firm is unlikely to lose all shareholders' equity only when it allocates partial capital to safe assets. In the worst case (a null return from a risky investment), the equity value can remain equivalent to the number of risk-free assets.

Nevertheless, the scale of investment is limited by shareholders' capital, which, to some extent, constrains the firm's further development. From the other perspective, the firm cannot buffer against negative cash flow shocks and protect shareholders' wealth unless it allocates all capital to safe assets at time $t = 0$. Therefore, the manager must be risk-averse to any investment.

By introducing a credit line, the firm can engage in investment management more efficiently by adjusting capital structure and/or asset allocation against different states. In a good state, external funding enables the firm to expand the risky investment to gain an excess return at $t = 1$. In the bad state, the firm can buffer against the anticipated income shortfalls by shrinking the drawdown scale and lowering the proportion of risky assets. However, the firm still confronts the possibility of default risk once it has obligations. In this situation, the shareholders' equity may decrease or even face liquidation to guarantee debt payment. Consequently, using credit lines contributes to asset management in different states but is a trade-off in corporate operations.

4.3 The Model

We now enrich the concepts in the previous example and build up a theoretical framework. An important foundation of our framework is the financial intermediation model of Allen et al. (2015). They develop a structure in which banks utilize both equity and deposits to invest in risky assets. We introduce three innovations to Allen et al. (2015)'s model. First, we shift the model from bank-base to firm-base and explore the profit-seeking behaviour of individual firms. Second, we switch the source of capital from deposits to banks' credit lines. Third, we allow the firm to hedge its risky project with risk-free assets. These innovations characterize the firm's liquidity management based on conjunct decisions of credit line utilization and asset allocation.

4.3.1 Basic Framework

The objective of modelling is to maximize shareholders' equity value given two decisions: the utilization of lines of credit and the allocation of assets. Assume a one-period economy, $t = 0, 1$. A firm possesses an original amount of equity value E_0 from shareholders. The manager of the firm plans to finance a project with credit lines from banks. Supposed that the firm can obtain total committed credit lines for M_0 and utilize a fraction ϕ_0, the withdrawal of the lines $\phi_0 M_0$ would become a debt L_0 maturing at $t = 1$ and the remaining lines would be $(1 - \phi_0)M_0$. Receiving the borrowing at the beginning, the manager decides to allocate all the capital from both liability and shareholders' equity to either cash holdings C_0 or the project I_0. According to the balance sheet equation, the original endowment of the firm can be expressed as:

$$C_0 + I_0 = L_0 + E_0 \tag{4.1}$$

where I_0 is the risky assets from the firm's investment in a project and C_0 is the risk-free assets, namely, cash holdings. Given the equation 4.1, we can define I_0 as a proportion η_0 of the total assets equal to the RHS, while C_0 can also be rewritten as the proportion $(1 - \eta_0)$ of the RHS.

Suppose that there is free entry into credit lines, and the firm can borrow at any amount up to the limitation. At the maturity $t = 1$, the expenses on the credit line are the interest of the drawdowns and the commitment fee of maintaining the undrawn credit lines. Thus, the debt amount that the firm incurs should be

$$L_1 = \underbrace{(1 + r_m)\phi_0 M_0}_{\text{Debt Payment}} + \underbrace{r_u(1 - \phi_0)M_0}_{\text{Commitment Fee}} \tag{4.2}$$

where r_m is the interest rate of the drawdowns and r_u is the unit commitment fee of the undrawn credit lines. Meanwhile, the firm obtains a return on both types of assets. Although the firm possesses a certain level of productivity and its expected return on investment is sufficiently high, it still faces a random shock in the cash flow. Let u denotes the cash flow shock that a firm may suffer. The shock is uniformly distributed on the support $[0, R]$ in which the maximum shock R is greater than two, indicating that the expected shock $R/2 > 1$ and the firm can recoup the expected return from the project. Moreover, the shock term is embedded with the p.d.f. $1/R$ and the c.d.f. u/R.

Following Nikolov et al. (2019), I parameterize the firm's production function using a Cobb-Douglas style with unit labour. Then, the output I_1 at $t = 1$ will be

$$I_1 = \underbrace{u}_{\text{Random Shock}} \underbrace{\overline{I_1}}_{\text{Expected Yield}} \tag{4.3}$$

in which

$$\overline{I_1} = \underbrace{\bar{A}}_{\text{Productivity}} (\underbrace{\eta_0}_{\text{Risky Fraction}} \underbrace{(\phi_0 M_0 + E_0)}_{\text{Total Assets}})^{\alpha} \tag{4.4}$$

In Eq. 4.4, $\bar{A}$ represents the idiosyncratic productivity and $0 < \alpha < 1$ stands for the elasticity.[4] Back to Eq. 4.3, the firm's production yield involves an uncertain part, the

[4] α is also the capital share in production defined by Nikolov et al. (2019).

random cash flow shock u, and a certain part $\overline{I_1}$ derived from the average productivity $\bar{A}$, the elasticity α, and risky assets $\eta_0(\phi_0 M_0 + E_0)$. Although the firm has an expected yield at $t = 1$ based on its endowments (internal), it must suffer the market shock (external). To buffer against this market shock, the firm can allocate the remaining capital $(1 - \eta_0)(\phi_0 M_0 + E_0)$ into risk-free assets. Thus, these safe assets will generate risk-free returns as

$$C_1 = \underbrace{(1 + r_f)}_{\text{Interest Rate}} \underbrace{(1 - \eta_0)}_{\text{Risk-Free Fraction}} \underbrace{(\phi_0 M_0 + E_0)}_{\text{Total Assets}} \tag{4.5}$$

where r_f is the risk-free rate of return.

Since the firm invests in a risky project, the shareholders' equity is insecure. If the incurred shock u is relatively low so that the firm needs to use all its equity to repay the debt, it will be closed to bankruptcy. To find the bankrupt boundary, we assume a specific shock value u_B that defines the equity E_1 at $t = 1$ equal to null. Combining with the balance sheet equation provides a *bankruptcy threshold equation* as:

$$C_1 + I_1 - L_1 = 0. \tag{4.6}$$

Given Eq. 4.3, we rearrange Eq. 4.6 and obtain the expression of the bankruptcy boundary u_B as:

$$u_B = \frac{L_1 - C_1}{\overline{I_1}} = \frac{(1 + r_m)\phi_0 M_0 + r_u(1 - \phi_0)M_0 - (1 + r_f)(1 - \eta_0)(\phi_0 M_0 + E_0)}{\bar{A}\left(\eta_0\left(\phi_0 M_0 + E_0\right)\right)^{\alpha}}. \tag{4.7}$$

It implies that when any shock happens below this boundary (that is, $u < u_B$), the shareholders' equity value will reduce to negative and lead to firm bankruptcy. Given this, firms manage to keep this boundary as low as possible in order to increase the possibility of survival.[5] Consequently, they will either reduce the difference between future liabilities and cash holdings, $L_1 - C_1$ or increase the expected yield of investment, $\overline{I_1}$. In other words, to avoid confronting bankruptcy, firms need to enhance their repayment abilities and productivity.

Since $\overline{I_1}$ is positive, the sign of u_B mainly depends on the sign of the difference between the future liabilities and cash holdings, $L_1 - C_1$. The positive sign of $L_1 - C_1$ shows that the firm cannot repay its liabilities by draining cash pooling. In this way, there is, to some extent, harm to the shareholders' equity value. On the contrary, the negative sign of $L_1 - C_1$ shows the firm's sufficient ability to pay debt payment without any harm to its equity.

[5]From the view of financial risk management, u_B works similarly to value-at-risk, which defines the possible financial losses. In our cases, u_B defines the highest financial risk that a firm can take.

4.3.2 Profit Optimization

Embedded with shareholders' equity and banks' credit lines, the firm chooses a portfolio of the credit line usage ϕ_0 and risky assets η_0 to maximize the expected profits Π. The expression for Π is given in the Appendix 4A. We begin with the optimization problem given by

$$\max_{\phi_0,\eta_0} \Pi = \int_{u_B}^{R} (\underbrace{\bar{A}u\left(\eta_0\left(\phi_0 M_0 + E_0\right)\right)^{\alpha}}_{\text{Risky Investment}} + \underbrace{\left(1+r_f\right)\left(1-\eta_0\right)\left(\phi_0 M_0 + E_0\right)}_{\text{Cash Holdings}} \\ - \underbrace{\left(\left(1+r_m\right)\phi_0 M_0 + r_u\left(1-\phi_0\right)M_0\right)}_{\text{Liabilities}})\frac{1}{R}du - \underbrace{\left(1+\rho\right)E_0}_{\text{Shareholder Value}} \tag{4.8}$$

subject to

$$0 \leq \phi_0 \leq 1,$$

and

$$0 \leq \eta_0 \leq 1.$$

where u_B has an expression in Eq. 4.7 and it locates within the support $[0, R]$. The firm chooses a portfolio of ϕ_0 and η_0 to maximize its expected shareholders' equity value at $t = 1$ less the original one. The first term in Eq. 4.8 is the return on both assets less the debt payment. It is only available when $u \geq u_B$ and the firm stays solvent. If $u < u_B$, the firm would go bankrupt and receive nothing. The second term in Eq. 4.8 is the opportunity cost for shareholders to provide capital to the firm.

4.3.3 Calibration

We use numerical simulation to obtain the feasible solution of Eq. 4.8. Our calibration is displayed in Table 4.1. We assume that the firm has a risk-neutral preference. It possesses an endowment of production technology which can generate high revenue ($\bar{A} = 1.25$) in units but gain reducing returns to scale ($\alpha < 1$). Meanwhile, the firm is embedded with capital ($E_0 = 0.15$) from shareholders, and it can access banks' credit lines ($M_0 = 1$) freely. Once it raises funds from credit line drawdowns, its leverage ratio would change within the range from 0% to 87% (1/1.15), and its proportion of equity to total assets would move from 100% to 13%. This assumption covers almost all the firms from our empirical analysis (Cerrato et al. 2023).

Since the firm faces market risk of its product, it would maximize the expected

Table 4.1. **Parameterization**

This table shows the calibration of model parameters. The first column shows the description of each parameter. The second column shows the symbolic notation of the parameters. The third column shows the corresponding numeric values.

Description	Notation	Value
Output Elasticity	α	0.5
Average Productivity	$\bar{A}$	1.25
Shareholders' Equity Value at $t = 0$	E_0	0.15
Total Committed Credit Lines	M_0	1
Risk-free Rate of Return	r_f	3%
Interest Rate of Credit Line Drawdowns	r_m	7%
Commitment Fee of Undrawn Credit Lines	r_u	4%
Shock Upper Boundary	R	2.1
Opportunity Cost of Shareholders	ρ	10%

value of the profit with respect to its choices of risky investment and cash holdings. For the risk-free rate, our baseline calibration $r_f = 0.03$, which is much lower than the interest rate of credit line drawdowns $r_m = 0.07$. It can prevent the firm's arbitrage opportunity. In the meantime, the fee for maintaining the undrawn credit lines is slightly higher than the risk-free rate ($r_u = 0.04 > 0.03$) but lower than the interest rate ($r_u = 0.04 < 0.07$). It is also an opportunity cost for the firm to use external liquidity. When it comes back to the market risk, we calibrate the upper limit of the range of the uniform distribution to be slightly greater than two ($R = 2.1 > 2$). At last, the opportunity cost of shareholders should be greater than the interest rate ($\rho = 0.1 > 0.07$), and shareholders should always have a chance to merely provide loans.

Figure 4.2A illustrates the profit function in Eq. 4.8. The concave surface exhibits a trade-off between the credit line usage and the asset allocation where both all-in (high ϕ_0 and high η_0) or overcautious (low ϕ_0 and low η_0) decisions cannot generate the maximum profit. The former decision may suffer a great cost of borrowing, which cannot be covered with a return on investment, and the latter may also incur the expense of maintaining credit lines. The contour plot in Figure 4.2B demonstrates that approaching the maximum profit requires the sizes of both utilization and allocation greater than half. Moreover, if the firm wants to withdraw more credit lines, it should reduce the scale of risky investment and vice versa. Given the calibration, the optimal portfolio of the utilization and allocation $(\phi_0^*, \eta_0^*) = (0.71, 0.75)$ can generate the maximum profit $\Pi^* = 0.4109$.

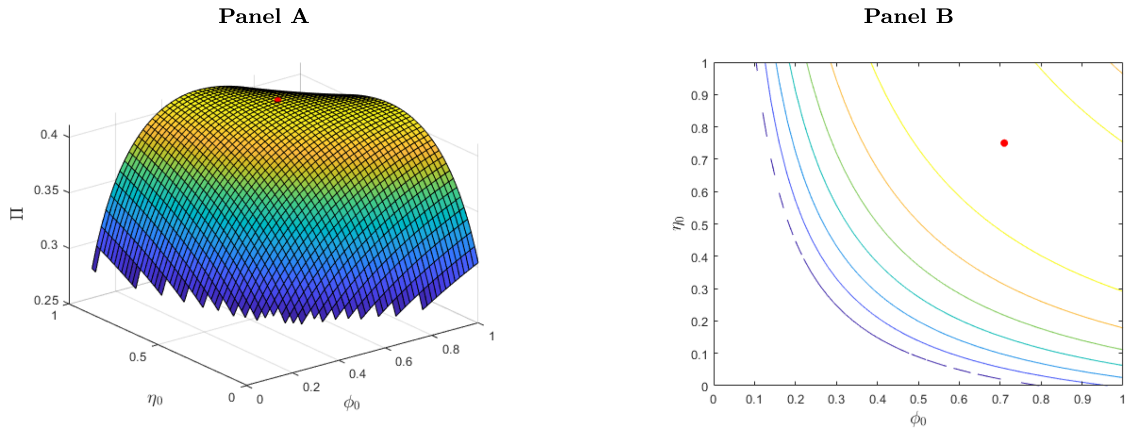


Figure 4.2. 3D-Surface and Counter Plots of Calibrated Profit Function.

This figure plots the 3D surface and counterplots of the calibrated profit function over the credit line usage (ϕ_0) and asset allocation (η_0) space. The left graph is the 3D plot. The jagged edge is due to the numerical simulation of the feasible region. Over the choice of utilization and allocation, the firm confronts a trade-off between the cost of drawdowns and the gains in a risky investment. The red spot shows the optimal choice as well as the maximum profit. The right graph is the counterplot. The contour lines' colours represent the profit's value, where the brighter the colour, the higher the value. There is a salient channel between the utilization and the allocation at the optimal level, which means the larger the utilization, the smaller the proportion of risky investment. The red spot shows the optimal portfolio of utilization and allocation.

4.3.4 Profit versus Credit Line Usage

We explore the reaction of profit to the utilization of credit lines. Given a target of risky investment, managers can adjust the credit line usage to fit the profit maximization policy. Figure 4.3 shows the process of the adjustment. If the proportion of risky assets is already at the optimal level (that is, $\eta_0^* = 0.75$), raising credit line usage from 21% to 71% would bring an increase of 13% in the profit. However, overusing credit lines, like increasing the utilization from 71% to 100%, would decrease the gain by 2%. It suggests that a relatively high level of investment (namely, 75% of assets are risky) exposes the firm to high market risk. The overuse of credit lines would make the firm suffer from excessive costs of debt and weakened corporate profitability.

Because of different factors, such as transaction cost and asset management strategy, adjusting asset allocation is unattainable or costly for a firm. In this way, the firm would confront two cases: 1) holding excessive cash ($\eta_0 < \eta_0^*$); 2) holding insufficient cash ($\eta_0 > \eta_0^*$). The blue lines in Figure 4.3 depict the former case. As the investment is conservative, the firm can retain cash holdings to hedge both the cost of credit line drawdowns and the market risk of investment. Nevertheless, the existing investment proportion cannot generate high profits for the firm. The firm must increase the credit line usage, which, in turn, enhances the default risk. The yellow lines in Figure 4.3 illustrate the latter case. An aggressive investment would bring the firm a high profit by drawing fewer credit lines than in the former case, but a large proportion of risky assets would simultaneously make the firm vulnerable to liquidity shocks. Moreover, overusing credit lines would lead to a decline in profit by nearly 10%. It suggests that a high investment position would produce higher market risk and less room for error in using credit lines.

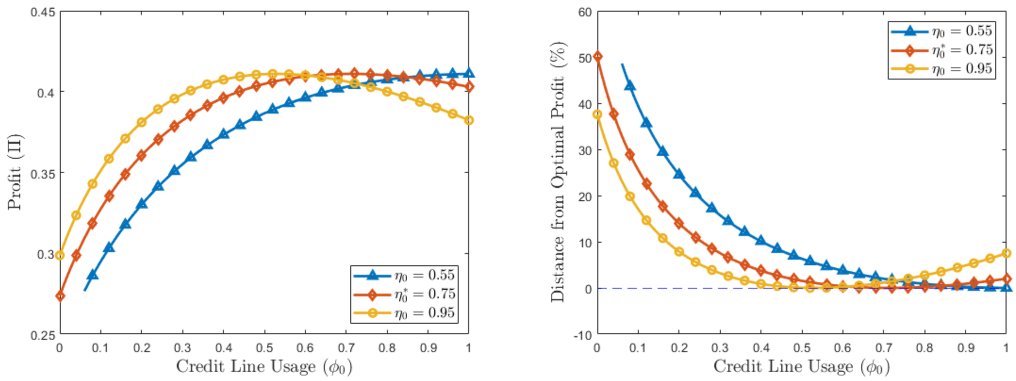


Figure 4.3. Profit versus Credit Line Usage.

This figure plots the corporate profit against credit line usage (ϕ_0) given different proportions of risky assets ($\eta_0 = 0.55, 0.75, 0.95$). The left plot shows the profit in response to the changes in credit line usage. The right plot shows the potential increase (%) when the credit line usage is changed to an optimal level. The red lines in both plots indicate the optimal investment level (η_0^*).

Figure 4.4 shows that if a firm can manage its assets and capital structure frictionlessly, a joint adjustment of credit line utilization with asset allocation would effectively improve profitability. In responding to each level of credit line usage, the firm can modify its asset allocation to an optimal ratio. This modification would enhance the profit up to 50% when it increases the utilization from 10% to around 50%. The joint adjustments would lead to an average 5.5% increase in the firm's profit. However, additional drawdowns above 50% cannot generate a salient growth in the gain with a simultaneous adjustment in asset allocation. The rationale may be that the benefit of using credit lines for profit generation is constrained by the firm's productivity and the cost of debt.

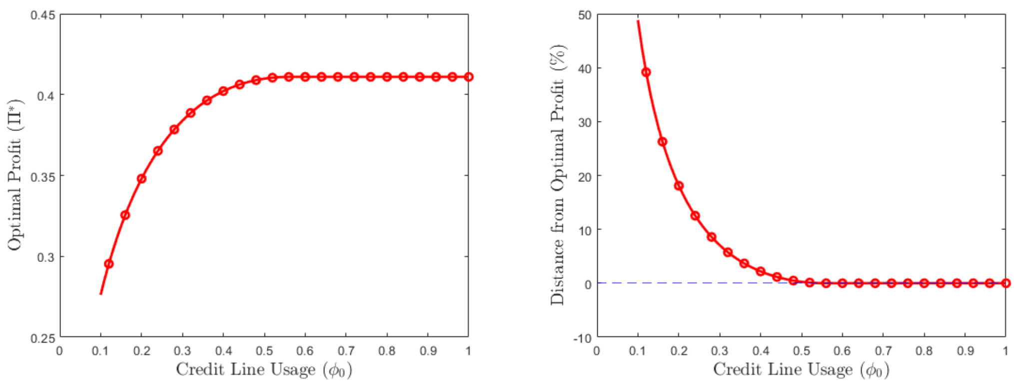


Figure 4.4. Maximum Profit versus Credit Line Usage.

This figure plots the available maximum of corporate profit against credit line usage (ϕ_0). The left plot shows the maximum profit in response to the change in credit line usage. The right plot shows the potential increase (%) when the credit line usage is changed to an optimal level.

4.4 Extension

In this section, we relax the assumption of some parameters of our basic framework and explore how the corporate profit reacts to these factors by choosing a portfolio of credit line utilization and asset allocation.

4.4.1 Interest Rate of Drawdowns

We study the response of the profit to the cost of borrowing credit lines. Particularly, we set the interest rate of drawdowns r_m as a variable moving within the support $[0, 0.1]$.

We begin with Figure 4.5, which shows the change in the maximum profit that a firm can achieve with the change in the interest rate. As r_m increases from null to a high level at 10%, the maximum profit drops by 14% (=0.065/0.465). It suggests that given the optimal decision, the firm's profits overreact to the cost of borrowing. Note that there exists a corner at $r_m = 7\%$ where the effect of interest rate on the maximum profit reduces even if the interest rate increases. It might be the case that the firm shifts its strategy of using credit lines when the cost is unaffordable.

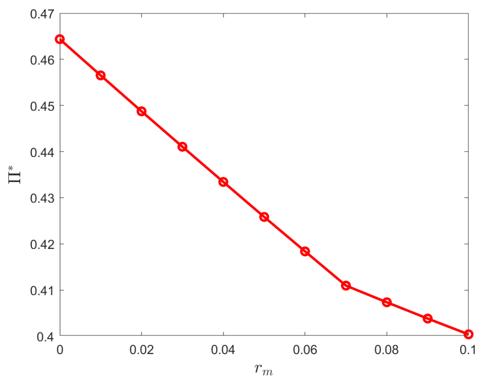


Figure 4.5. Maximum Profit versus Cost of Drawdowns.

This figure shows the maximum profit that a firm can obtain given the change in the interest rate of credit line drawdowns. The decreasing solid red line illustrates a negative relationship between the maximum profit and the interest rate. The corner at $r_m = 0.07$ shows that the effect of the interest rate on the maximum profit reduces when r_m is at a high level.

Next, we fix a decision variable and find the optimal values of the profit and the other decision variables. The top and the bottom left plots in Figure 4.6 show similar pictures. When one of the decision variables (η_0 or ϕ_0) is fixed, the maximum profit has a linearly negative relationship with the interest rate. The top right plot in Figure 4.6 illustrates that with the cost of borrowing decreasing, the optimal credit line usage keeps elevating. This negative association theoretically proves Cooperman et al. (2023)'s suggestion that the fall in loan rate will encourage borrowers to draw down more credit lines. On the other side, it seems that if a firm decides to maintain a cash holding level $(1 - \eta_0)$, it should reduce its reliance on banks' credit lines when the cost of borrowing rises. Nevertheless, the bottom right plot provides a different resolution, one in which the firm chooses to preserve its capital structure and enlarge the proportion of risky assets. Although the firm faces an increasing market risk, it hedges the cost of debt by allocating more capital to risky investments, which further exposes it to the risk.

Compared with the variable of asset allocation, credit line usage overreacts to changes in interest rates. As the cost of debt increases from null to 10%, the optimal value of the utilization drops by 30% (=0.3/1), while the one of the allocation changes by 8% (=0.06/0.72). It implies that amending capital structure may be more difficult than amending asset allocation in response to the movement of the interest rate.

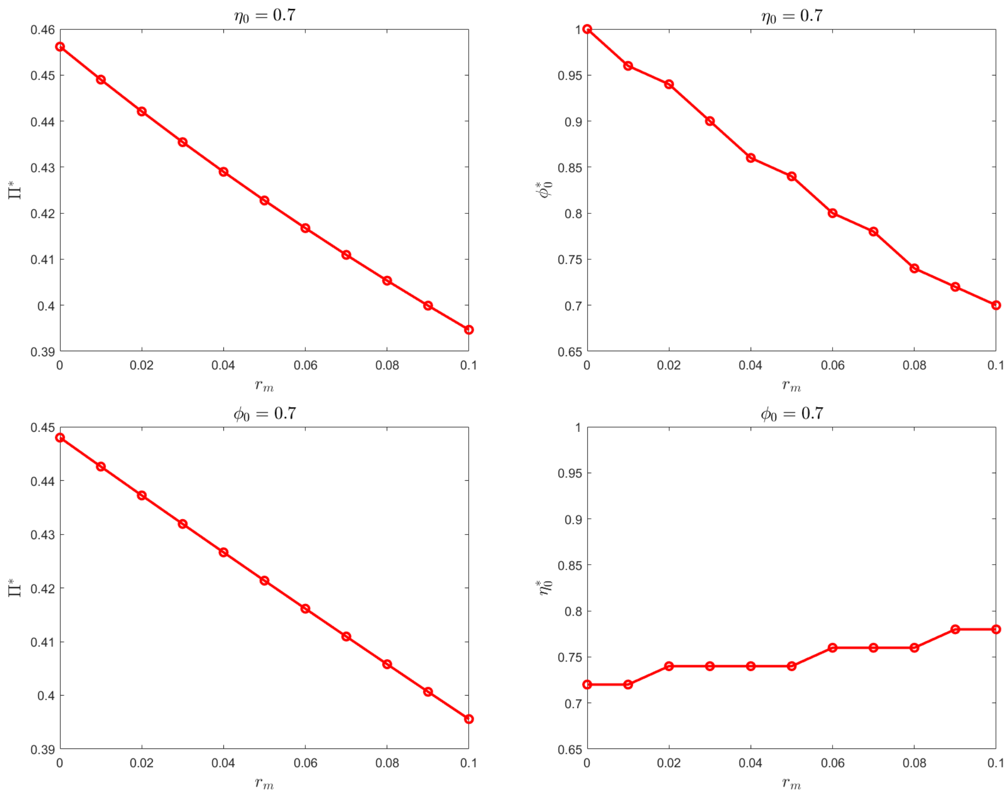


Figure 4.6. Maximum Profit versus Cost of Drawdowns (η_0 or ϕ_0 fixed).

This figure plots the response of the maximum profit and the optimal variable to the interest rate of credit line drawdowns given either the asset allocation (η_0) or the credit line usage (ϕ_0) constant. The upper two plots are with the allocation fixed ($\eta_0 = 0.7$). The lower two plots are with the utilization fixed ($\phi_0 = 0.7$).

4.4.2 Total Credit Lines

To study the model's implications with respect to banks' credit lines, we relax the calibration of total committed credit lines and set it as a variable on the support $[0, 1.2]$. By this mean, the equity-to-total-asset ratio could move from 100% to 11% if the firm always utilizes the credit line fully. Meanwhile, the maximum leverage ratio could rise from 0% to 89%.

Even if a firm can have any committed amount of credit lines from banks, it does not mean it should hold as many credit lines as possible. Figure 4.7 documents this implication. Provided that the firm can always enjoy the utmost profit by an optimal selection of utilization and allocation, it would benefit from even a small increment of credit lines compared with null funding from banks. However, this benefit would marginally decrease due to the debt payment burden. Whatever the percentage of credit line usage would lead to interest expense on credit line drawdowns, commitment fee on undrawn credit lines, or both costs. Once it exceeds the firm's (expected) profitability generated from the assets, it would be unaffordable to maintain such a large credit line size. Therefore, our simulation in Figure 4.7 shows the optimal amount of committed credit lines should be 0.4 when the firm should utilize all the credit lines and allocate all the capital to risky investment ($\phi_0^* = 1, \eta_0^* = 1$).

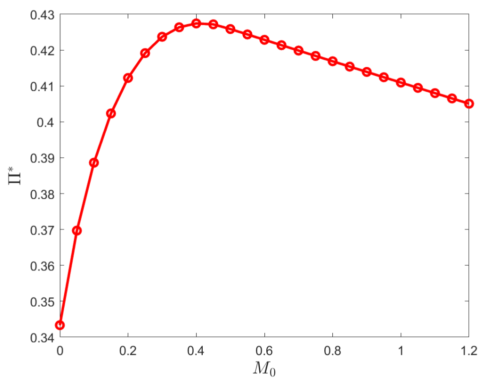


Figure 4.7. Maximum Profit versus Total Committed Credit Lines.

This figure shows a firm's maximum profit given the change in total committed credit lines. The solid red line illustrates the concavity between the maximum profit and the total committed credit lines. The peak value is $M_0 = 0.4$, which means that possessing more committed credit lines cannot benefit the firm's profit maximization strategy.

Similar to the previous section, we fix one of two decision variables and explore the other one associated with total credit lines. The upper two plots in Figure 4.8 document the situation where the firm sticks to an investment proportion. The top left plot shows a similar picture as Figure 4.7, but the peak value appears later. Note that there is a missing value when total credit lines are very few. It suggests that given a high level of investment, the firm must rely on external funding. Otherwise, it would face bankruptcy. The top right plot shows that the firm should utilize all the lines until the committed amount is very high. The bottom two plots, retaining a certain level of utilization, in Figure 4.8 are similar to the top ones, but there is no missing value where total credit lines are few. This is because amending asset allocation is more manipulative for the manager than adjusting capital structure.

As a comparison with Figure 4.7, the left two plots in Figure 4.8 display a later appearance of optimal total credit lines. Firms which have reservations about their risky investment strategy ($\eta_0 < 1$) or their credit line usage strategy ($\phi_0 < 1$) would sacrifice a part of the profit and rely more on banks' credit lines. In other words, radical firms, which would utilize all credit lines and invest all capital into risky projects, have less reliance on these external financing sources than conservative firms, which would not utilize all or invest all.

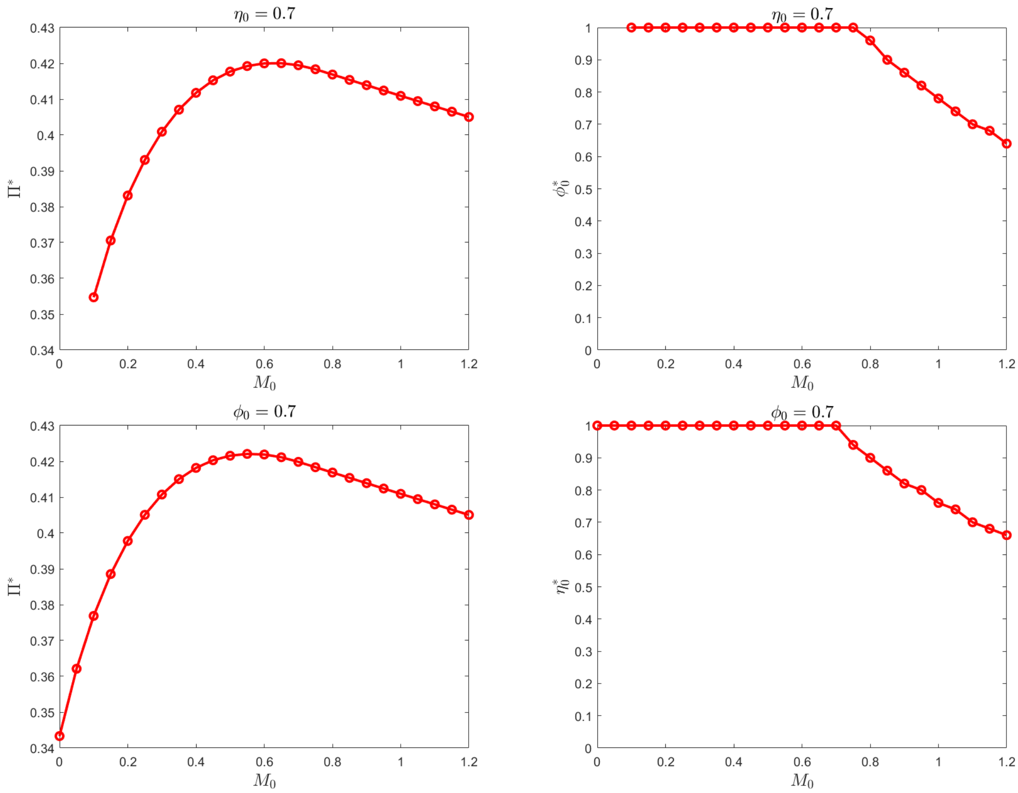


Figure 4.8. Maximum Profit versus Total Committed Credit Lines (η_0 or ϕ_0 fixed).

This figure plots the response of the maximum profit and the optimal variable to the total committed credit lines given either the asset allocation (η_0) or the credit line usage (ϕ_0) constant. The upper two plots are with the allocation fixed ($\eta_0 = 0.7$). The lower two plots are with the utilization fixed ($\phi_0 = 0.7$).

4.5 Alternative Model

Shareholders' equity maximization is a foundation that dominates a firm's investment decisions. Otherwise, shareholders would not risk their wealth and permit an aggressive investment. However, the literature focuses on asset generation instead of shareholders' wealth. In this section, we construct an alternative model and test whether the asset optimization policy is reliable.

4.5.1 Basic Framework

Similar to Eq. 4.8, we establish a model that a firm chooses an optimal portfolio of credit line utilization ϕ_0 and asset allocation η_0 to maximize its total assets (risk-free and risky assets). The asset maximization problem has an expression as follows:

$$\max_{\phi_0,\eta_0} \Pi_A = \int_{u_B}^{R} (\underbrace{\bar{A}u\left(\eta_0\left(\phi_0 M_0 + E_0\right)\right)^{\alpha}}_{\text{Risky Investment}} + \underbrace{\left(1+r_f\right)\left(1-\eta_0\right)\left(\phi_0 M_0 + E_0\right)}_{\text{Cash Holdings}})\frac{1}{R}du - \underbrace{\left(\phi_0 M_0 + E_0\right)}_{\text{Capital}} \quad (4.9)$$

subject to

$$0 \leq \phi_0 \leq 1,$$

and

$$0 \leq \eta_0 \leq 1.$$

where u_B has the same expression as in Eq. 4.7. The firm maximizes its total assets at time $t = 1$ net of the original capital from banks' credit line drawdowns and shareholders' equity. Different from Eq. 4.8, the first term in Eq. 4.9 considers no debt payment. However, it still requires the firm to stay solvent ($u \geq u_B$). The second term in Eq. 4.9 represents the original funds equivalent to the total assets at time $t = 0$.

4.5.2 Calibration

We use the calibration of parameters in Table 4.1 and obtain the available solution of the asset function in Eq. 4.9. Figure 4.9A illustrates the asset function. The surface displays that a large credit line usage and a small fraction of risky investment can generate the optimal value. With the calibration, the optimal portfolio of the usage, the allocation, and the maximum assets should be $(\phi_0^A, \eta_0^A, \Pi_A^*) = (1, 0.18, 0.4071)$. Figure 4.9B explicitly shows the optimal combination (ϕ_0^A, η_0^A). This result recommends that a firm may draw down almost all the credit lines and put the majority into safe assets, like cash and cash equivalents, to achieve the asset maximization goal.

Compared with the numerical solution in Eq. 4.8 ($\Pi^* = 0.4109$), the one in Eq. 4.9 is smaller ($\Pi_A^* = 0.4071 < 0.4109$). It means that the asset maximization policy cannot generate the maximum profit for the firm. Moreover, plugging the portfolio (ϕ_0^A, η_0^A) into the profit function (Eq. 4.8) provides the value $\Pi = 0.3804$ which is 7% $((0.4109 - 0.3804)/0.4109)$ lower than the maximum profit.

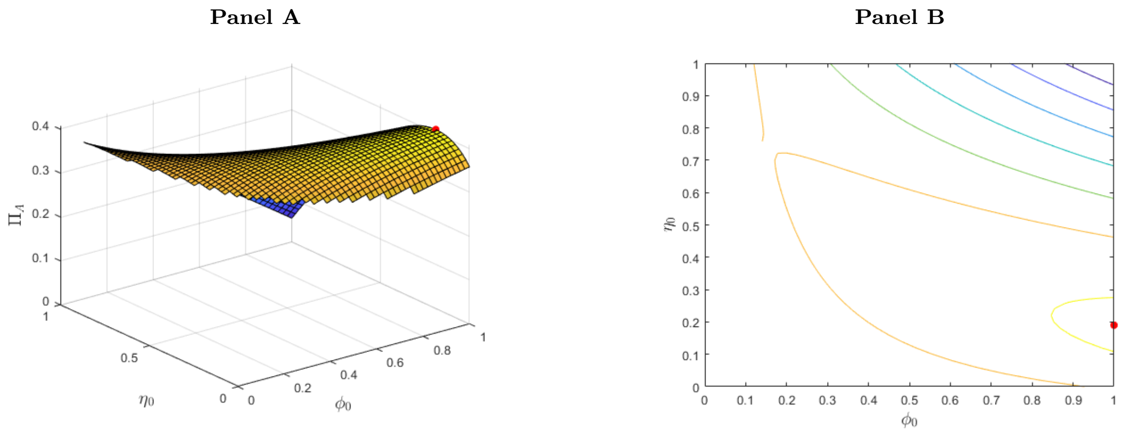


Figure 4.9. 3D-Surface and Counter Plots of Calibrated Asset Function.

This figure plots the 3D surface and counterplots of the calibrated asset function over the credit line usage (ϕ_0) and asset allocation (η_0) space. The left graph is the 3D plot. The jagged edge is due to the numerical simulation of the feasible region. The red spot shows the optimal choice and the maximum increment of total assets. The right graph is the counterplot. The colours of the contour lines represent the value of the total assets, where the brighter the colour, the higher the value. The red spot shows the optimal portfolio of utilization and allocation.

4.6 Productivity and Market Risk

The optimal behaviour of firms' credit line drawdown is our main interest. We want to explore the relationships between credit line usage, idiosyncratic productivity, and aggregate market risk.

4.6.1 Stable Market

At first, we explore the relationship in a normal market where firms can get moderate rewards ($R/2 > 1$). Figure 4.10 shows the relationships between firms' optimal behaviour of credit line utilization (ϕ_0^*) and their productivity ($\bar{A}$). We fix the asset allocation (η_0) to 0.7 and keep the variation term (R) as the original endowment in Table 4.1. The red line represents the baseline model ($\bar{A} = 1.25$). An intuitive view is that firms can fully withdraw credit lines ($\phi_0^* = 1$) until the total committed lines are excessive ($M_0 \geq 0.75$). The downward bend suggests that firms cannot balance the high cost of the 100% credit line usage (which also means a high debt level) and the yield of current productivity. Precisely, firms choose to reduce utilization as a trade-off. Besides, the decreasing line appears beyond the bend ($0.75 \leq M_0 \leq 1.2$), indicating that firms must lower the usage level to offset the increasing cost of drawdowns as the banks' lines of credit increase.

Based on the benchmark calibration, we modify the productivity term to investigate the firms' optimal behaviours of credit line usage. The blue line represents a 20% reduction in productivity. The unit value ($\bar{A} = 1$) means that a \$1 investment can yield only \$1 product. An early appearance of the downward bend suggests that productivity reduction weakens firms' ability to deal with debt overhangs. Nevertheless, the yellow line representing a 20% increment in productivity ($\bar{A} = 1.5$) shows that a high yield level prevents firms from debt overhang and allows them to draw down all credit lines from any committed amount. In short, Figure 4.10 implies that the higher productivity, the higher the ability to borrow from banks' credit lines.

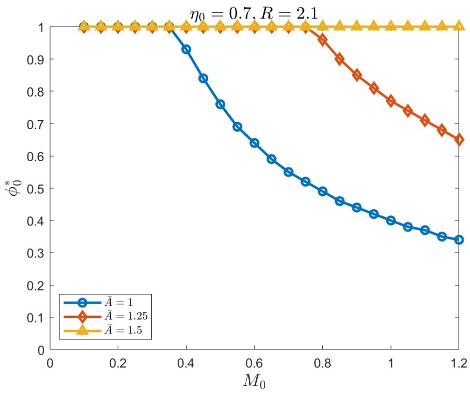


Figure 4.10. Optimal Credit Line Usage versus Total Committed Credit Lines (High-Yield Firms).

This figure plots the optimal drawdown behaviour against different total committed credit lines by firm types. The asset allocation (η_0) and the shock term (R) are fixed. The horizontal axis is the total committed lines (M_0), while the vertical one is the optimal credit line usage (ϕ_0^*). Firms are diversified based on the productivity term ($\bar{A}$). The blue line represents firms with unit productivity ($\bar{A} = 1$). The red line represents our baseline model ($\bar{A} = 1.25$). The yellow line represents firms with relatively high productivity ($\bar{A} = 1.5$).

What if the productivity is very low? Given the asset allocation and the variation term unchanged, we embed three values below the unit in the productivity term ($\bar{A} = 0.1, 0.35, 0.6$). These values imply that for low-yield firms, a \$1 investment can yield, for example, only a \$0.1 product. Figure 4.11 depicts these three scenarios. Unexpectedly, three lines (red, blue, and yellow) overlap, which makes the optimal behaviours of credit line utilization indifferent among different productivity levels. This unified behaviour pattern suggests that firms with insufficient yield have no diversified choices and follow the same routine of borrowing. When the banks' committed lines are low, they can withdraw a moderate amount. However, the withdrawals become extremely limited when the committed lines are high.

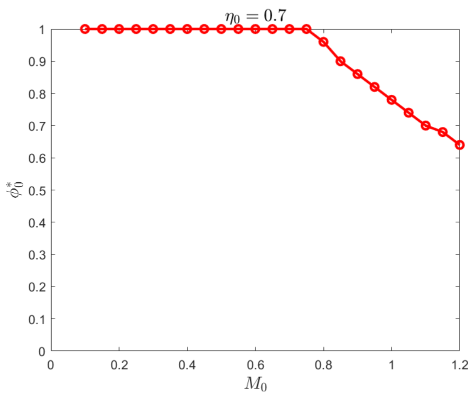


Figure 4.11. Optimal Credit Line Usage versus Total Committed Credit Lines (Low-Yield Firms).

This figure plots the optimal drawdown behaviour against different total committed credit lines by firm types. The asset allocation (η_0) and the shock term (R) are fixed. The horizontal axis is the total committed lines (M_0), while the vertical one is the optimal credit line usage (ϕ_0^*). Firms are diversified based on the productivity term ($\bar{A}$). The blue line represents firms with very low productivity ($\bar{A} = 0.1$). The red line represents firms with relatively higher productivity ($\bar{A} = 0.35$). The yellow line represents firms with productivity close to the unit ($\bar{A} = 0.6$).

We want to explore how firms optimize their credit line utilization behaviours against shock. In this way, we relax the assumption of the shock term (R). A considerable value of the shock term ($R/2 \gg 1$) is equivalent to a large yield variation, meaning firms can recoup their investment and obtain rewards from markets. Inversely, a small shock term ($R/2 \ll 1$) indicates a high-risk market that little can firms recover from their investment.

Figure 4.12 shows the reaction of the high-yield firms ($\bar{A} = 1.25$) to the shock variation. In a *bear* market ($R < 1$), firms' optimal credit line usage (ϕ_0^*) is negatively associated with their committed lines (M_0). The returns on investment and safe assets cannot burden a high cost of credit line drawdowns. As the shock term increases, firms can upgrade their utilization levels with more capacity for debt repayment. In a *bull* market ($R > 2.5$), they can always draw down all credit lines.

Firms with low productivity have a much simpler pattern. Figure 4.13 shows the behaviour of low-yield firms ($\bar{A} = 0.35$). Intuitively, the negative association between optimal credit line usage (ϕ_0^*) and committed lines (M_0) is invariant along the changes in shock term. It again shows evidence that low-yield firms have limited drawdown choices whether in *bear* or *bull* markets.

4.6.2 High-Risk Market

When the market risk is exceptionally high, firms have entirely different behaviours, regardless of their productivity. This market signals firms that they will likely lose all

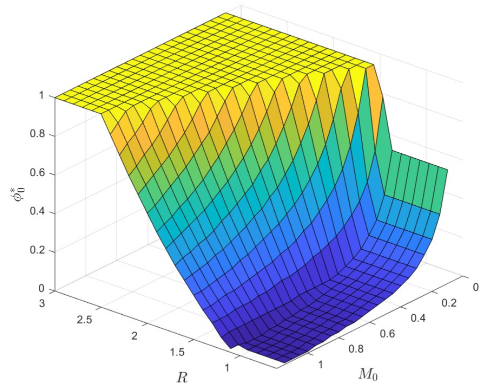


Figure 4.12. 3D-Plot of High-Yield Firms.

This 3D plot shows the high-yield firms' optimal drawdown behaviour against both total committed credit lines and shock variation. The productivity is fixed ($\bar{A} = 1.25$). The x-axis is the total committed credit lines (M_0). The y-axis is the shock term (R). The z-axis is the optimal credit line usage (ϕ_0^*). The brighter the colour, the higher the usage.

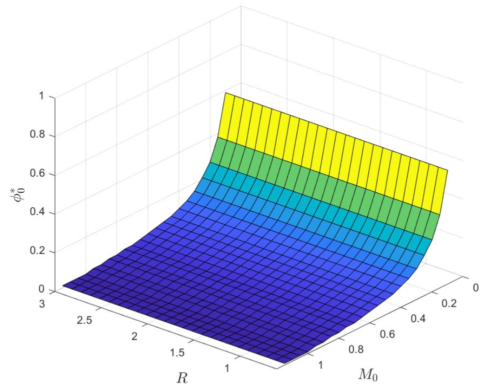


Figure 4.13. 3D-Plot of Low-Yield Firms.

This 3D plot shows the low-yield firms' optimal drawdown behaviour against both total committed credit lines and shock variation. The productivity is fixed ($\bar{A} = 0.35$). The x-axis is the total committed credit lines (M_0). The y-axis is the shock term (R). The z-axis is the optimal credit line usage (ϕ_0^*). The brighter the colour, the higher the usage.

their investment. To capture this situation in our theoretical model, we can embed R with a value close to zero. For example, based on its investment function, a firm expects that investing \$1 can usually yield a \$1.25 product. However, a high-risk market ($R/2 = 0.1$) will eventually allow the firm to sell its product at \$0.125 (\$1.25×0.1), which makes the sales fail the firm's expectations and, even worse, the cost of production. In 2020, the COVID-19 pandemic led to governments' lockdown policies, which made the aggregate risk rocket in markets. Under such circumstances, how do firms with different productivity levels react?

We start with the high-yield firms ($\bar{A} = 1.25$) and explore how they perform in an exceptionally high-risk market ($0 \leq R \leq 0.6$). Figure 4.14 shows the optimal drawdown behaviour under this scenario. The platform in the diagram indicates that firms observing an increasing aggregate risk (R decreases) choose to withdraw all their credit lines if they can obtain as many committed lines as possible (M_0 increases). This "panic borrowing" shows the irrational behaviour of high-yield firms: even though the risk of debt overhangs (or solvency risk) is increasing, they keep borrowing from banks' credit lines. It may be the corporate nature of high productivity that *permits* them to draw down credit lines. On the contrary, the fewer committed lines (M_0 decreases), or the smaller the aggregate risk (R increases), the more suppression of the "panic borrowing". A simple pattern like Figure 4.13 appears, even if the market is still risky ($0.5 \leq R \leq 0.6$).

Next, we move to low-yield firms ($\bar{A} = 0.35$). Figure 4.15 illustrates how these firms behave in the extremely high-risk market. The platform indicating 100% credit line usage merely appears when total committed lines are relatively low ($M_0 < 0.3$). The higher the aggregate risk (or the lower the R), the wider the platform. It implies that low-yield firms have irrational "panic borrowing" only if their credit lines committed by banks are below a small threshold ($M_0 = 0.3$). As markets become riskier, this threshold moves backwards, and firms have less room to behave irrationally. Besides, the quarte-pipe-ramp shape in Figure 4.15 shows that low-yield firms will reach a high level of credit line usage once they obtain additional committed lines from banks ($M_0 \geq 0.3$). This shape is evenly distributed along the shock term (R), suggesting that the firms still follow the simple pattern that the usage is negatively related to the total committed credit lines regardless of how risky the market is.

Interestingly, both high- and low-yield firms behave similarly when the market recovers. In Figures 4.14 and 4.15, we can find the simple pattern arises as the shock term (R) increases, especially when firms' total committed credit lines (M_0) are small. This pattern seems to convey a conventional behaviour: when the market is risky but restorable, firms with different productivity levels reduce their credit line usage against increasing line commitments.

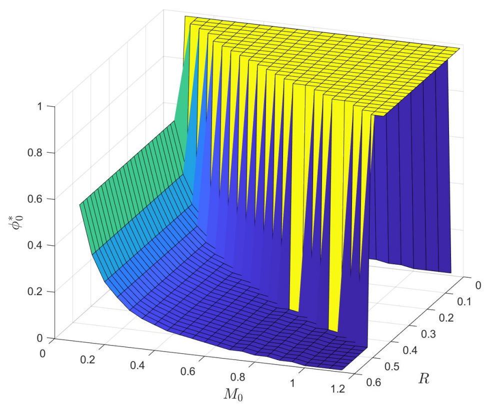


Figure 4.14. 3D-Plot of High Risk (High-Yield Firms).

This 3D plot shows the high-yield firms' optimal drawdown behaviour against both total committed credit lines and shock variation. The productivity is fixed ($\bar{A} = 1.25$). The x-axis is the total committed credit lines (M_0). The y-axis is the shock term (R). The z-axis is the optimal credit line usage (ϕ_0^*). The brighter the colour, the higher the usage.

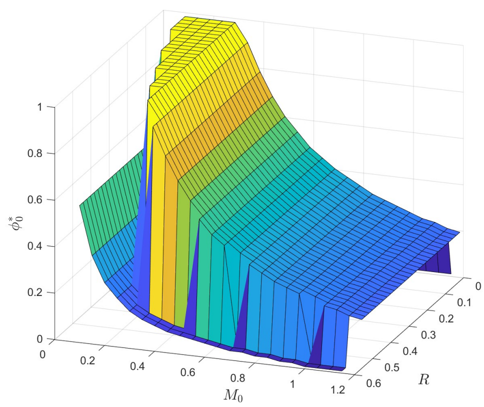


Figure 4.15. 3D-Plot of High Risk (Low-Yield Firms).

This 3D plot shows the low-yield firms' optimal drawdown behaviour against both total committed credit lines and shock variation. The productivity is fixed ($\bar{A} = 0.35$). The x-axis is the total committed credit lines (M_0). The y-axis is the shock term (R). The z-axis is the optimal credit line usage (ϕ_0^*). The brighter the colour, the higher the usage.

4.7 Covenant Violation

Compared with the total amount of credit lines (the sum of drawn and undrawn credit), the unused amount plays a special role in financial risk management. In a corporate annual report, taking Mercedes-Benz Group as an example, a credit line is an instrument for liquidity management (Mercedes-Benz Group 2022). Its purpose is to enable the firm to meet its payment obligations at any time. In this way, undrawn capacity actually plays a role in cash-pooling. However, undrawn lines are often constrained through interfering covenant violation. In this section, we develop the baseline model to capture the effect of covenant violation on wealth generation.

4.7.1 Model Set Up

Therefore, we can rewrite the bankruptcy threshold equation (Eq. 4.6) as:

$$(C_1 + N_1) + I_1 - L_1 = 0 \tag{4.10}$$

where N_1 denotes undrawn capacity with an expression as:

$$N_1 = \lambda(1 - \phi_0)M_0.$$

$0 \leq \lambda \leq 1$ denotes the *undrawn flexibility*, representing the freedom of the firm accessing undrawn credit lines. The higher the value of λ, the more freedom (or less covenant constraints) to draw the lines. The value equal unit shows that the firm can freely access banks' credit. Rearranging Eq. 4.10 provides a new bankruptcy boundary considering undrawn credit lines:

$$u_B^{'} = \frac{L_1 - C_1 - N_1}{\overline{I_1}} \quad , \tag{4.11}$$

This expression implies that considering undrawn capacity, the possibility of survival increases, i.e., $u_B^{'} < u_B$, with $\lambda > 0$. In other words, as long as a firm can access undrawn lines, it can use credit lines to reduce its default risk.[6]

Plugging the new bankruptcy boundary back to the profit function optimization

[6] An explicit way to show the negative association between the bankruptcy boundary and the access freedom is the first-order condition $\frac{\partial u_B^{'}}{\partial \lambda} = -\frac{(1-\phi_0)M_0}{\overline{A}(\eta_0(E_0+M_0\phi_0))^{\alpha}} \leq 0$ when all parameters are non-negative.

provides a new expression as:

$$\max_{\phi_0,\eta_0} \Pi_U = \int_{u_B'}^{R} \left(\bar{A}u\left(\eta_0\left(\phi_0 M_0 + E_0\right)\right)^{\alpha} + \left(1 + r_f\right)\left(1 - \eta_0\right)\left(\phi_0 M_0 + E_0\right)\right.$$
$$\left. - \left(\left(1 + r_m\right)\phi_0 M_0 + r_u\left(1 - \phi_0\right) M_0\right)\right)\frac{1}{R}du - \left(1 + \rho\right) E_0 \quad (4.12)$$

subject to

$$0 \leq \phi_0 \leq 1,$$

and

$$0 \leq \eta_0 \leq 1.$$

To illustrate the profit function, we apply the calibration as in the previous section. Besides, we assume λ as 0.9 and endow a firm with nearly free access to undrawn credit lines. Figure 4.16 shows the 3D surface and the contour plot, respectively. Compared with Figure 4.2, an explicit optimization appears around the peak $(\phi_0^*, \eta_0^*) = (0.59, 0.94)$. It suggests that a firm can allocate most of its capital to risky assets with an increase in the possibility of survival (or a decrease in liquidity risk).

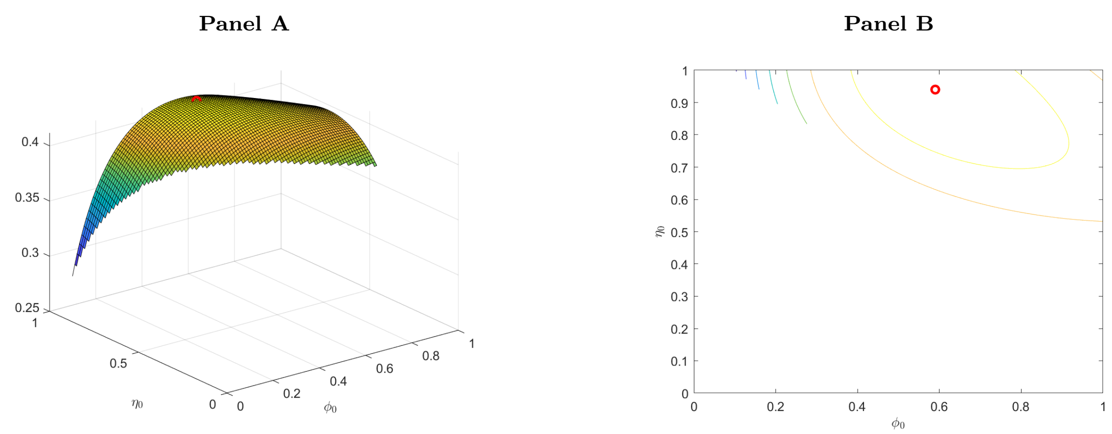


Figure 4.16. 3D-Surface and Counter Plots of Profit Function Considering Covenant Violation.

This figure plots the 3D surface and counterplots of an alternative calibrated profit function over the credit line usage (ϕ_0) and asset allocation (η_0) space. The function considers the covenant violation context. The left graph is the 3D plot. The jagged edge is due to the numerical simulation of the feasible region. Over the choice of utilization and allocation, the firm confronts a trade-off between the cost of drawdowns and the gains in a risky investment. The red spot shows the optimal choice as well as the maximum profit. The right graph is the counterplot. The contour lines' colours represent the profit's value; the brighter the colour, the higher the value. There is a salient channel between the utilization and the allocation at the optimal level, which means the larger the utilization, the smaller the proportion of risky investment. The red spot shows the optimal portfolio of utilization and allocation.

4.7.2 The Effect of Covenant Violation

Does the access to undrawn credit lines affect the firm's profit? As λ defines how freely a firm can use undrawn credit, the value approaching unit can give the firm sufficient space for survival. In this way, the corporate profit should benefit from the lower liquidity risk and reach a higher position. To investigate this issue, we relax the setting of λ and explore the response of maximum profit to it. Figure 4.17 shows the results. Out of expectation, the maximum profit is negatively related to λ. It suggests that more freedom of accessing undrawn credit lines leads to lower profit.

Taking the partial difference of the profit function in Eq. 4.12 with respect to λ yields:

$$\frac{\partial \Pi_U}{\partial \lambda} = -\frac{\lambda M_0^2 \left(1-\phi_0\right)^2}{\overline{A}R\left(\eta_0\left(E_0+M_0\phi_0\right)\right)^{\alpha}}. \tag{4.13}$$

As all parameters in the numerator and denominator are non-negative, the right-hand side of Eq. 4.13 are non-positive, given the negative sign. Even if both ϕ_0 and η_0 are of optimization to maximize profit, the non-positive partial difference still holds.

Given the above mathematical evidence of a negative relationship between λ and profit Π_U, there is also economic meaning. Regarding the cash-pooling role of undrawn credit lines, a firm can use this liquidity management instrument to hedge liquidity risk. The more cash-like the credit lines are, the more willing the firm is to keep them unused. Meanwhile, the firm has to suffer from a larger commitment fee (usually a proportion of the undrawn amount) and a larger opportunity cost. When it chooses to retain the undrawn credit lines, it abandons the opportunity to finance investment through drawdowns. Consequently, it cannot generate more profit through investment.[7]

4.8 Empirical Estimation

In this section, we will empirically estimate our theoretical model. Since the model in Eq. 4.8 has no closed-form solution, we use an estimation technique based on simulation. Particularly, we estimate the unknown structural parameters using the method of simulated moments (MSM, or SMM) in Hennessy & Whited (2007). This method selects the parameters which can minimize the distance between the simulated

[7]There is a puzzle that firms' annual reports seem to diminish their credit line drawdowns and emphasize their undrawn amount (e.g. Mercedes-Benz Group (2022)). Instead of using credit lines for (re)financing, they prefer to strengthen investors' faith in managing liquidity risk through undrawn credit lines.

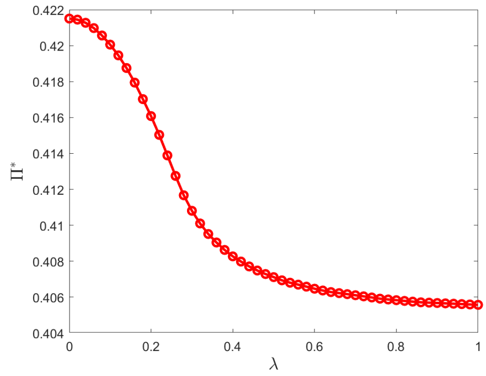


Figure 4.17. Maximum Profit versus Undrawn Flexibility (λ).

This figure plots the response of the maximum profit to the undrawn flexibility of undrawn credit lines.

moments from a theoretical model and the moments from a real database.

4.8.1 Structural Estimation Model Settings

Based on the settings in Eq. 4.8, let θ denotes a vector of unknown structural parameters, including an output elasticity (α), the total factor productivity (A), the risk-free rate of return (r_f), the interest rate of borrowing credit lines (r_m), the commitment fee of maintaining unused lines (r_u), and the opportunity cost of shareholders (ρ). Within the real database, we have the output variable Y_i (e.g. profit), the input variables X_i (e.g. credit line usage, asset allocation, book value, and total lines of credit), and N observations. Given the unbiased assumption, the moment conditions should satisfy $E\left[m\left(Y_i, X_i, \theta\right)\right] = 0$, where

$$m\left(Y_i, X_i, \theta\right) = \begin{pmatrix} Y_i - E\left(Y_i|X_i, \theta\right) \\ X_i\left[Y_i - E\left(Y_i|X_i, \theta\right)\right] \\ Y_i^2 - E\left(Y_i^2|X_i, \theta\right) \end{pmatrix}.$$

Now, we simulate the moment conditions by mimicking discrete i.i.d. random shock $u_s \sim U\left(0, R\right)$ $(s = 1, 2, ..., S)$. Let two expectations in the matrix be $\hat{Y}_i\left(X_i, u_s, \theta\right) = E\left(Y_i|X_i, \theta\right)$ and $\left[\hat{Y}_i\left(X_i, u_s, \theta\right)\right]^2 = E\left(Y_i^2|X_i, \theta\right)$. Then, we construct S samples to estimate each expectation. That is,

$$\begin{aligned}\hat{Y}_i\left(X_i, u_s, \theta\right) = S^{-1}\sum_{s=1}^{S}[\bar{A}u_s\left(\eta_0\left(\phi_0 M_0 + E_0\right)\right)^{\alpha} + \left(1 + r_f\right)\left(1 - \eta_0\right)\left(\phi_0 M_0 + E_0\right) \\ - \left(\left(1 + r_m\right)\phi_0 M_0 + r_u\left(1 - \phi_0\right)M_0\right)] - \left(1 + \rho\right)E_0. \quad (4.14)\end{aligned}$$

We define that

$$Q_N(\theta) \quad = \left(N^{-1}\sum_{i=1}^{N} E\left[m\left(Y_i, X_i, \theta\right)\right]\right)' W_N \left(N^{-1}\sum_{i=1}^{N} E\left[m\left(Y_i, X_i, \theta\right)\right]\right).$$

and find the SMM estimator $\hat{\theta}$ to minimize $Q_N(\theta)$. That is,

$$\hat{\theta} \quad = \arg\min_{\theta} Q_N(\theta).$$

For simplicity, we define the weighting matrix as an identity matrix, meaning that $W_N = I_N$.

4.8.2 Data

We collect non-financial, Euro-Area firms with credit line information during 2018:Q4 – 2020:Q3 from Bloomberg. The empirical sample size is 1159. The corporate financial information from Bloomberg includes credit line usage, total committed credit lines, total assets, book value of shareholders' equity, and cash and cash equivalents. Given these variables from actual data, we can approximate the model input, including credit line utilization (ϕ_0), asset allocation (η_0), shareholders' equity value (E_0), and total committed credit lines (M_0). Table 4B1 in Appendix 4B describes how to construct these variables.

Our primary interest is the changes in corporate production during this period when it was the COVID-19 pandemic. Two terms from the theoretical model, the output elasticity (α) and the average productivity ($\bar{A}$), can capture the production characteristics. To better understand this issue, we also split our sample and estimate a subset of the parameters for before-COVID (2018:Q4 – 2019:Q4) and during-COVID (2020:Q1 – 2020:Q3) periods. Through these estimations, we keep the shock term (R) unchanged to focus on the variation in productivity.

The model is solved via iteration based on the *fminsearch* function in The MathWorks©, which applies the "Nelder-Mead simplex direct search" algorithm to find the numerical solution (Lagarias et al. 1998). we use grid-search to try different values of parameters $\tilde{\theta}(\alpha, \bar{A}, r_f, r_m, r_u, \rho) = \theta$. Given each combination of parameter values from grid searching, we insert them into the policy function and iterate for 100 steps to find the optimal values. Then, we collect these optimal values from all combinations and find the best ones to minimize the distance between the simulated and actual data.

Table 4.2 shows the simulated variables to mimic the real-world data variables.

Table 4.2. **The Mimicks of Real-World Data Variables**

This table shows the simulated moments which are used to match the actual moments.

Actual Terms	Simulated Terms	Source
Total Assets	$\phi_0 M_0 + E_0$	Eq. 4.5
Cash Holdings	$(1+r_f)(1-\eta_0)(\phi_0 M_0 + E_0)$	Eq. 4.5
Investments	$\bar{A}[\eta_0(\phi_0 M_0 + E_0)]^\alpha$	Eq. 4.4
Liabilities	$(1+r_m)\phi_0 M_0 + r_u(1-\phi_0)M_0$	Eq. 4.2
Profit	$\int_{u_B}^{R} (\bar{A}(\eta_0(\phi_0 M_0 + E_0))^\alpha u + (1+r_f)(1-\eta_0)(\phi_0 M_0 + E_0)$	Eq. 4.8
	$-((1+r_m)\phi_0 M_0 + r_u(1-\phi_0)M_0))g(u)du - (1+\rho)E_0$	

4.8.3 Estimation Results

In order to locate $\theta = \{\alpha, \bar{A}, r_f, r_m, r_u, \rho\}$, we try to match the first and second moments of the profit, cash holdings, investments, liabilities, the covariance between profit and cash holdings, and the covariance between investments and liabilities. All variables are normalized by total assets. The mean and variance of profit contain the information of all parameters, especially the shareholders' opportunity cost (ρ). However, the mean and variance of cash holdings are still informative about the risk-free rate (r_f). Similarly, the mean and variance of liabilities are informative about the loan rate (r_m) and the commitment fee (r_u). The mean and variance of investments are informative about the productivity ($\bar{A}$) and the output elasticity (α). The covariance terms can tell the conjunction effect among these variables.

Table 4.3 includes the estimation results of the full sample. Panel A compares the actual moments with the simulated ones. The model is able to match the balance sheet quantities closely, especially the variance of profit, the mean and variance of cash holdings, the mean of investments, and the covariance between profit and cash holdings. Meanwhile, the mean of profit, the mean and variance of liabilities, and the covariance between investments and liabilities match weakly. In both actual and simulated data, the average cash holdings account for merely 8.95% of the total assets (versus 5.83% in the simulation). The proportion is relatively minor compared with the investments, suggesting that firms are generally aggressive in investing in fixed (or illiquid) assets.

Panel B of Table 4.3 reports the estimates of the parameters. The estimated output elasticity (α) is around 0.64. Since we consider merely capital input in our production function, this estimation suggests that a 1% increase in risky assets would lead to approximately a 0.64% increment in production. In addition, the average aggregate productivity ($\bar{A}$) is roughly 0.11. Both terms have minor standard errors.

Table 4.3. **Simulated Moment Estimation for the Full Sample**

This table presents the simulated moment estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the fourth quarter of 2018 to the third quarter of 2020. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel shows actual and simulated moments. The second panel reports the estimated structural parameters, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments		
	Actual Moments	Simulated Moments
Average Profit	0.0102	0.4193
Variance of Profit	0.0108	0.0360
Average Cash Holdings	0.0895	0.0583
Variance of Cash Holdings	0.0054	0.0024
Average Investments	0.9105	0.8131
Variance of Investments	0.0053	0.0609
Average Liabilities	0.4056	0.0563
Variance of Liabilities	0.1400	0.0108
Covariance of Profit and Cash Holdings	0.0006	0.0018
Covariance of Investments and Liabilities	-0.0073	0.0048

Panel B: Parameters Estimates					
α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6385	0.1133	0.0004	0.0123	0.0109	0.1129
(0.0015)	(0.0003)	(0.000001)	(0.0001)	(0.00002)	(0.0005)

Next, we turn to the pandemic's impact on firms' production. Tables 4.4 and 4.5 report parameter estimates before and during COVID-19, respectively. Table 4.4, we find that the estimations of the before-COVID sub-sample are close to the ones of the full sample. The output elasticity is nearly 0.65, while the average productivity is around 0.14. Using the during-COVID sub-sample in Table 4.5, the elasticity declines to 0.12, meaning that a 1% increase in risky assets can only bring a 0.12% output growth. Meanwhile, the average productivity decreases by 60.8% ($1 - 0.0531/0.1354$) compared to the pre-COVID period. It suggests that the aggregate outputs grow by 0.05% with a 1% increase in aggregate inputs. This result is consistent with the finding in Cerrato et al. (2023) that the social distancing policies caused by the COVID-19 crisis hurt firms' productivity.

Table 4.4. **Simulated Moment Estimation for Pre-COVID Period**

This table presents the simulated moment estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the fourth quarter of 2018 to the fourth quarter of 2019, the pre-COVID period. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel shows actual and simulated moments. The second panel reports the estimated structural parameters, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments		
	Actual Moments	Simulated Moments
Average Profit	0.0087	0.4151
Variance of Profit	0.0013	0.0314
Average Cash Holdings	0.0872	0.0558
Variance of Cash Holdings	0.0056	0.0020
Average Investments	0.9128	0.8127
Variance of Investments	0.0056	0.0536
Average Liabilities	0.4180	0.0584
Variance of Liabilities	0.1237	0.0117
Covariance of Profit and Cash Holdings	0.0004	0.0009
Covariance of Investments and Liabilities	-0.0073	0.0053

Panel B: Parameters Estimates					
α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6544	0.1354	0.0004	0.0107	0.0105	0.1295
(-0.0008)	(-0.0003)	(-0.000001)	(-0.00004)	(-0.00001)	(-0.0004)

One challenge to the interpretation of productivity is the absence of a measure of the labour factor in our data. Our Cobb-Douglas production function assumes a unit labour input. At the same time, estimating the average productivity term ($\bar{A}$) through real-life data indeed consists of labour and other multi-factors. According to Cerrato et al. (2023), we use *Exposure* that measures the work flexibility in the pandemic as a

Table 4.5. **Simulated Moment Estimation for COVID Period**

This table presents the Simulated Moment Estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the first quarter of 2020 to the third quarter of 2020, the COVID period. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. The first panel shows actual and simulated moments. The second panel reports the estimated structural parameters, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments

	Actual Moments	Simulated Moments
Average Profit	0.0143	0.4313
Variance of Profit	0.0363	0.0491
Average Cash Holdings	0.0958	0.0656
Variance of Cash Holdings	0.0047	0.0034
Average Investments	0.9042	0.8141
Variance of Investments	0.0047	0.0822
Average Liabilities	0.3721	0.0503
Variance of Liabilities	0.1833	0.0084
Covariance of Profit and Cash Holdings	0.0011	0.0042
Covariance of Investments and Liabilities	-0.0077	0.0033

Panel B: Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.1182	0.0531	0.0005	0.0079	0.0225	0.0833
(-0.022)	(-0.0012)	(-0.00001)	(-0.0002)	(-0.0004)	(-0.0008)

proxy for the labour factor. To explore the impact of labour on productivity, we split our sample at the firms' pandemic exposure median. *High Exposure* defines firms with *Exposure* above the median, while the rest are *Low Exposure*. Then, we estimate the model parameters separately for the high- and low-exposure firms.

The results are in Table 4.6. Panel A presents the comparison between actual and simulated moments across different types of firms, which shows similar results to Panel A of Table 4.3. Panels B and C of Table 4.6 report the parameters of high- and low-exposure firms, respectively. Considering the full period, high-exposure firms have average productivity ($\bar{A}$) at 0.1068, lower than the one of low-exposure firms (0.1203). Regarding the output elasticity (α), high-exposure firms also possess a lower value than low-exposure ones ($0.6492 < 0.6570$). Thus, firms' exposure level has a close and negative connection to their overall productivity.

Tables 4.7 and 4.8 compare high- and low-exposure firms before and during the pandemic, respectively. Regarding productivity, we find that high-exposure firms' output elasticity (α) dropped from 0.67 before the pandemic to 0.39 during the crisis, a 41.8% decline. The aggregate productivity ($\bar{A}$) incurred a 53.8% decrease from 0.13 before the pandemic. Nevertheless, low-exposure firms merely experienced a 3% decline in output elasticity and a 20.3% decrease in aggregate productivity during the pandemic. Although the COVID-19 crisis attacked both firms, low-exposure firms with high work flexibility suffered less productivity reduction than high-exposure ones.

Another finding is that the opportunity cost of high-exposure firms (ρ) reduced by 27.6%, while the cost of low-exposure firms inversely rose by 2.72%. Moreover, it was higher among high-exposure firms before the COVID-19 crisis ($0.1270 > 0.0992$), but it changed to the opposite situation during the crisis ($0.0929 < 0.1019$). As the opportunity cost of shareholders can capture investors' preference, it shows a shift in external funding from investors: Compared with pre-pandemic, they prefer to invest in firms with flexible working conditions in the pandemic era. Although this implication seems predictable, we quantify this shifting process.

Table 4.6. **Estimates of Pandemic Exposure: Full Sample**

This table presents the Simulated Moment Estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the fourth quarter of 2018 to the third quarter of 2020. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Firms are grouped by *High-* and *Low-Exposure*, according to their *Job Done At Home* indices (Dingel & Neiman 2020). The first panel shows actual and simulated moments of both types of firms. The second and the third panels report the estimated structural parameters of *High-Exposure* and *Low-Exposure* firms, respectively, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments

	High-Exposure		Low-Exposure	
	Actual Moments	Simulated Moments	Actual Moments	Simulated Moments
Average Profit	0.0101	0.4159	0.0104	0.4260
Variance of Profit	0.016	0.0285	0.0011	0.0503
Average Cash Holdings	0.0985	0.0652	0.0729	0.0449
Variance of Cash Holdings	0.0055	0.0028	0.0047	0.0012
Average Investments	0.9015	0.8007	0.9271	0.8374
Variance of Investments	0.0054	0.0433	0.0047	0.0942
Average Liabilities	0.4216	0.0621	0.3765	0.0449
Variance of Liabilities	0.1133	0.0111	0.1880	0.0102
Covariance of Profit and Cash Holdings	0.0007	0.0024	0.0004	0.0007
Covariance of Investments and Liabilities	-0.0056	0.0049	-0.0098	0.0049

Panel B: High-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6492	0.1068	0.0004	0.0126	0.0111	0.1090
(0.0017)	(0.0004)	(0.000002)	(0.0001)	(0.00002)	(0.0005)

Panel C: Low-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6570	0.1203	0.0004	0.0126	0.0109	0.1100
(0.0009)	(0.0004)	(0.000001)	(0.00004)	(0.00001)	(0.0004)

Table 4.7. **Estimates of Pandemic Exposure: Pre-COVID Period**

This table presents the Simulated Moment Estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the fourth quarter of 2018 to the fourth quarter of 2019, the pre-COVID period. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Firms are grouped by *High-* and *Low-Exposure*, according to their *Job Done At Home* indices (Dingel & Neiman 2020). The first panel shows actual and simulated moments of both types of firms. The second and the third panels report the estimated structural parameters of *High-Exposure* and *Low-Exposure* firms, respectively, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments

	High-Exposure		Low-Exposure	
	Actual Moments	Simulated Moments	Actual Moments	Simulated Moments
Average Profit	0.0068	0.4116	0.0122	0.4224
Variance of Profit	0.0013	0.0240	0.0014	0.0460
Average Cash Holdings	0.0953	0.0619	0.0718	0.0432
Variance of Cash Holdings	0.0059	0.0023	0.0047	0.0012
Average Investments	0.9047	0.8003	0.9282	0.8382
Variance of Investments	0.0058	0.0367	0.0047	0.0868
Average Liabilities	0.4296	0.0636	0.3963	0.0477
Variance of Liabilities	0.0990	0.0119	0.1698	0.0110
Covariance of Profit and Cash Holdings	0.0004	0.0012	0.0004	0.0002
Covariance of Investments and Liabilities	-0.0059	0.0053	-0.0094	0.0057

Panel B: High-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6671	0.1305	0.0004	0.0110	0.0105	0.1270
(0.0015)	(0.0008)	(0.000002)	(0.0001)	(0.00003)	(0.001)

Panel C: Low-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6633	0.1186	0.0003	0.0137	0.0112	0.0992
(0.0004)	(0.0002)	(0.000001)	(0.00004)	(0.00001)	(0.0004)

Table 4.8. **Estimates of Pandemic Exposure: COVID Period**

This table presents the Simulated Moment Estimation of non-financial Euro-Area firms from Bloomberg. The sample period is from the first quarter of 2020 to the third quarter of 2020, the COVID period. Estimation is done with SMM, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Firms are grouped by *High-* and *Low-Exposure*, according to their *Job Done At Home* indices (Dingel & Neiman 2020). The first panel shows actual and simulated moments of both types of firms. The second and the third panels report the estimated structural parameters of *High-Exposure* and *Low-Exposure* firms, respectively, with standard error in parentheses. α is the output elasticity parameter. $\bar{A}$ is the average productivity. r_f, r_m, and r_u represent the risk-free rate of return, the loan rate of credit line drawdowns, and the commitment fee of undrawn credit lines, respectively. ρ is the shareholders' opportunity cost.

Panel A: Moments

	High-Exposure		Low-Exposure	
	Actual Moments	Simulated Moments	Actual Moments	Simulated Moments
Average Profit	0.0192	0.4291	0.0058	0.4352
Variance of Profit	0.0568	0.0419	0.0002	0.0619
Average Cash Holdings	0.1075	0.0750	0.0756	0.0491
Variance of Cash Holdings	0.0042	0.0044	0.0048	0.0013
Average Investments	0.8925	0.8020	0.9244	0.8352
Variance of Investments	0.0042	0.0637	0.0048	0.1145
Average Liabilities	0.3990	0.0576	0.3259	0.0375
Variance of Liabilities	0.1535	0.0085	0.2326	0.0081
Covariance of Profit and Cash Holdings	0.0014	0.0058	0.0002	0.0017
Covariance of Investments and Liabilities	-0.0050	0.0039	-0.0110	0.0028

Panel B: High-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.3883	0.0596	0.0007	-0.0068	0.0183	0.0920
(0.0201)	(0.0015)	(0.0001)	(0.0032)	(0.0012)	(0.0016)

Panel C: Low-Exposure Firms Parameters Estimates

α	$\bar{A}$	r_f	r_m	r_u	ρ
0.6411	0.0945	0.0004	0.0131	0.0116	0.1019
(0.0051)	(0.0008)	(0.000002)	(0.0001)	(0.0001)	(0.0007)

4.9 Conclusion

We construct and estimate a two-period model of corporate liquidity management. Firms can fund themselves from original shareholders' equity and credit line drawdowns. Then, the combination of reserving cash and investing in risky assets can generate maximum wealth and hedge shocks. We model revolving credit facilities as providing liquidity in the sense that they can be withdrawn on the investment need, but they are likely to increase firms' default risk. The economic mechanisms emerging in our model are thus trade-offs between the cost and the benefit of using credit lines and between hoarding cash and risky investment. We introduce these trade-offs into a flexible model of corporate financing and investment. Finally, we evaluate the rationalizing power by empirical data and structural estimation.

One limitation of our model setting is that firms can contract any amount of line commitments. Even though we show a threshold that firms cannot benefit any more from extra line commitments, banks may agree to lend a smaller amount due to firms' information and banks' financial health. In addition, it is important to consider corporate investment decisions in a dynamic way. We leave these tasks for future studies.

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Appendices

4A Model Set Up

The expected profit is derived from the difference between the future ($t = 1$) and the beginning ($t = 0$) values of shareholders' equity. According to the balance sheet equation and Eq. 4.2 across 4.5, we define

$$\mathbf{E}(E_1) \quad = \mathbf{E}(I_1 + C_1 - L_1)$$

to be the expectation of shareholders' equity value at $t = 1$ which is equivalent to the expected return on both assets (I_1 and C_1) less the debt payment (L_1). Since the return on investment has a shock term u which is a random variable uniformly distributed on $[0, R]$, the expectation of E_1should be expressed as

$$\mathbf{E}(E_1) = \quad \int_0^R (I_1 + C_1 - L_1)\tfrac{1}{R}du \tag{15}$$

where $1/R$ is the p.d.f of the shock distribution.

Before a firm obtains its profit, it must stay solvent till next period. Otherwise, the firm would obtain nothing and go bankrupt. The threshold of the solvent region ensures a non-negative shareholders' equity value, equivalent to

$$E_1 = \quad I_1 + C_1 - L_1 = 0.$$

Since C_1 and L_1 are known at the beginning time, the only uncertain term is the random variable in I_1. Therefore, the shock term u can drive the equity value equal to null. Given that, we assume the *threshold shock* u_B, with an expression in Eq. 4.7, as boundary which ensures that any $u > u_B$ can provide a positive equity value for the firm. Although u_B can be any real number in principle, we only consider the values within $[0, R]$ in our cases. By this means, the solvent region of the firm should be $u \in [u_B, R]$. We can rewrite Eq. 15 by changing the lower limit

$$\mathbf{E}(E_1) = \quad \int_{u_B}^R (I_1 + C_1 - L_1)\tfrac{1}{R}du. \tag{16}$$

There exists a opportunity cost for investors to be shareholders instead of loan lenders. The condition of being shareholders at the beginning is the promised return on equity (ROE), or opportunity cost ρ, greater than the loan interest rate. The *real* corporate profit should be the expected equity value at $t = 1$ (Eq. 16) net of the equity value at $t = 0$ plus the opportunity cost, expressed by

$$\Pi \quad = \int_{u_B}^R (I_1 + C_1 - L_1)\tfrac{1}{R}du - (1 + \rho)E_0$$

where Π represents the profit. Inserting the expression of L_1, I_1, and C_1 through Eq. 4.2 to 4.5 to the above formula, we can have the complete expression of the expected profit at $t = 1$. Solving the integral.

4B Variable Descriptions

Table 4B1. **The Construction of Model Input**

This table shows how to use variables from actual data to approximate the model input.

Input Variables	Notation	Description
Credit Line Utilization	ϕ_0	Equal to credit line usage. Credit line usage is the drawn proportion of total committed credit lines, equivalent to credit line drawdowns divided by total committed credit lines. Source: Bloomberg.
Asset Allocation	η_0	Equal to one minus cash holdings divided by total assets, where cash holdings are measured by cash and cash equivalents. It represents a firm's investments which are fixed (or illiquid) assets. Source: Bloomberg.
Shareholders' Equity Value	E_0	Equal to book value of shareholders' equity divided by total assets. Source: Bloomberg.
Total Committed Credit Lines	M_0	Equal to total committed credit lines divided by total assets. Source: Bloomberg.