European SMEs: Climate Risk, Financing and Ownership

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Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Abstract

This thesis presents a comprehensive study on the capital structure and climate risk of European small and medium-sized enterprises (SMEs). The first empirical chapter investigates the correlation between SMEs' leverage, ownership structure, and corporate risk, highlighting an inverted U-shaped relationship between ownership concentration and debt ratios, with significant disparities across different ownership structures. Family-owned enterprises and firms that operate in the same industry as their ultimate owner carry higher levels of financial debt, whereas government-controlled firms demonstrate low risk and low financial debt ratios.

The second and third chapters focus on the impact of climate risks on small and micro firm performance and default probability. Using comprehensive financial data and gridded weather data, we demonstrate that rising temperatures and extreme weather events significantly affect firm performance and default probability. The average operating income of a firm decreases by 6.8% per 1°C increase in yearly mean temperature, with micro and financially constrained firms exhibiting

increased vulnerability. Similarly, escalating temperature and intensive precipitation risk amplify a firm's default probability by 86.5 and 32.4 basis points, respectively, per standard deviation increase. We observe heterogeneous climate risk impacts across different ownership structures and industries, noting that ultimate owners functioning as managers can potentially mitigate these adverse effects.

This thesis, therefore, offers a multidimensional examination of SMEs, elucidating the complex interplay between financial leverage, ownership structure, and climate risk susceptibility. It contributes valuable insights to the economic climate literature and provides important implications for financial planning, risk management, and policy-making in the SME sector.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Small and medium-sized enterprises (SMEs) constitute a vital segment of the OECD region, representing approximately 99% of all businesses. These enterprises are not just prolific in number; they also significantly contribute to job creation, generating about 70% of all job opportunities. Further, SMEs contribute to 50% to 60% of value creation, a significant achievement considering their size (OCDE (2016b)). Their economic impact extends to developing economies as well, where they account for nearly half of the employment and one-third of the GDP. The contribution of SMEs to GDP increases beyond 50% when considering informal businesses (Teima et al. (2010)). According to the annual report of Commission (2021), SMEs account for over 99% of all businesses and provide two-thirds of total private sector employment in Europe. This dissertation explores the capital structure choices of SMEs and the climate risks they face. Specifically, it examines how ownership structure, as indicated by ownership concentration and ultimate ownership type, influences SMEs' financing choices. Furthermore, it scrutinizes how shifts in temperature and precipitation patterns impact SMEs' performance and default probability.

The initial empirical chapter of this dissertation delves into the determinants of the capital structure of European SMEs. It utilizes an extensive dataset from Orbis, encompassing approximately 0.6 million firms across 12 European countries, with SMEs constituting a significant majority (96%). This large and diverse dataset, superseding those employed in prior studies (Hall et al. (2004), Mac an Bhaird and Lucey (2010), López-Gracia and Sogorb-Mira (2008), Daskalakis et al. (2017), D'Amato (2020)), facilitates the generation of more generalized insights within the Eurozone economic context. In addition to traditional firm-specific determinants such as size, age, asset tangibility, profitability, and sales growth, we accord significant attention to firm-specific risk and ownership structure. Previous research on SMEs' capital structure largely overlooked controlling for firm-specific risk, opting instead to use profitability and size as rough proxies for firm risk. In this context, firms with higher profits and total assets are perceived as less risky (D'Amato (2020)). To conserve observation count, D'Amato (2020) calculates firm risk using the annual profit deviation from the average profit for a firm. However, the inclusion of future profit in this average calculation renders the firm-risk measure questionable. Our study measures firm risk using the three-year rolling volatility of a firm's profit, confirming the trade-off theory's prediction that firm risk negatively impacts capital structure (Kraus and Litzenberger (1973)). Furthermore, we differentiate between "good volatility" from "bad volatility" and find that when firm risk embodies the "good volatility", firms tend to utilize more debt.

Jensen and Meckling (1976) agent cost theory underscores the significance of ownership structure in determining capital structure. Both ownership concentration and the type of ultimate owner influence Type 1 and Type 2 agency costs, which correspond to conflicts between managers and owners, and conflicts involving majority shareholders, minority shareholders, and lenders, respectively. This study documents, for the first time in the context of European SMEs, a reverse U-shaped relationship between ownership concentration and leverage ratio, previously observed solely in large firms (Brailsford et al. (2002), de La Bruslerie and Latrous (2012), Lo et al. (2016)). It emerges that firms with a low level of ownership concentration are more likely to increase debt to secure their control rights. However, at high levels of ownership concentration, the firm's primary concern shifts to mitigating default risks associated with high financial leverage, leading to a reduction in debt usage. The study further highlights the pivotal role of the ultimate owner. Specifically, it finds that government-owned firms, due to their risk-averse tendencies, utilize significantly less debt and more trade credit, while family firms favor greater debt usage. For instance, the total debt-to-capital ratio of family firms is 16.7 percentage points higher than that of government firms.

In the subsequent empirical chapter, the study pivots towards the investigation of climate risk, a paramount issue confronting contemporary society. More specifically, it examines the potential impacts of global warming on the profitability of European small and micro firms. Dell et al. (2014) suggest that the adverse effects of global warming are more pronounced in developing countries as compared to their developed counterparts. In a similar vein, the study hypothesizes that small businesses are more susceptible to climate risks than larger firms, a premise evidenced by the negligible impacts of average temperature changes on the sales revenue and profits of large US firms (Addoum et al. (2020)). The concentration on small businesses stems from two primary reasons. Firstly, small businesses, due to their constrained resources and insufficient insurance coverage, might face higher adversity in adapting to climate change (Berkhout et al. (2006); Hoffmann et al. (2009)). Unlike large corporations with diversified operations and geographic reach, SMEs lack similar diversification against climate risk. Moreover, they might struggle to comprehend the intricacies of complex climate risk, further complicating their mitigation efforts (Weinhofer and Busch (2013)). Secondly, focusing on small and micro firms minimizes weather variable measurement errors as these firms are more location-concentrated, rendering temperature and precipitation data at the firm's headquarters more representative than for large firms. The study uncovers a significant impact of mean temperature and extremely hot days on firm profitability. It further identifies that smaller and financially constrained firms suffer disproportionately due to rising temperatures.

The third empirical chapter investigates whether the detrimental effects of climate change on firm performance could escalate to influence the default risk of the company. Previous studies on the implications of climate change for default risk remain scarce, particularly in the context of SMEs. To the best of our knowledge, no existing research addresses this issue in relation to SMEs. To circumvent the measurement issue highlighted in the second empirical test, this study concentrates on small and micro firms. Previous literature focusing on large firms generally applies Merton's distance to default (Merton (1974)) and Moody's CreditEdge data to assess the default risk amidst climate change, measuring climate change through carbon emission risk (Capasso et al. (2020), Kabir et al. (2021), Nguyen et al. (2023)) and ESG scores (Li et al. (2022)). However, both Merton's distance to default and Moody's CreditEdge data are unavailable for small firms as these measures necessitate daily stock price as a vital input. This study is pioneering in utilizing actual default events data to evaluate the default risk of small and micro firms in relation to climate change. We assess chronic physical risk via diverse temperature and precipitation metrics and discover that under-performance stemming from rising temperatures and intensive precipitation can ultimately lead to a firm's bankruptcy. Similar to the second empirical test, we find the negative impacts on default probability intensify for smaller, highly leveraged, and financially constrained firms. Across the second and third empirical chapters, we observe that the energy and utility sectors may remain unscathed by climate change.

This thesis addresses critical issues at the intersection of finance and environmental studies, focusing on the impact of capital structure, climate change, and physical climate risks on small and medium enterprises (SMEs) and micro firms in Europe. Drawing from foundational financial theories and contemporary environmental data, it significantly contributes to both disciplines.

In the domain of capital structure, my research revisits key theories—trade-off theory, pecking order theory, and agency cost theory—to explore the leverage determinants in SMEs across the Eurozone. One of the empirical studies in the thesis stands out for its comprehensive dataset of 625,483 companies across 12 European countries, emphasizing SMEs. It offers a more generalizable understanding of SME capital structures in the Eurozone and delves into the influence of ownership concentration and characteristics of ultimate owners on SME financing, providing new insights into SME capital structuring dynamics.

Shifting the focus to the physical risks of climate change, the thesis examines the impact of high temperatures on the performance of small and micro firms. By integrating high-resolution weather data with financial reports, it becomes the first systematic examination of the effects of increasing temperatures on the performance of European small and micro enterprises. My research reveals a significant decrease in a firm's operating income with a 1°C increase in mean temperature and investigates how firm size, financial constraints, and ownership structure affect a firm's resilience to climate risks.

Furthermore, the thesis extends to the impact of climate change on the default risk of SMEs. Leveraging temperature and precipitation data, I document a direct correlation between climate-related physical risks and the default probability of small and micro firms. This analysis highlights the increased vulnerability of firms with fewer assets, higher leverage ratios, and financial instability to climate risks, indicating varied impacts across different geographical regions and industrial sectors.

In conclusion, the thesis bridges a crucial gap between financial theory and the tangible impacts of climate change, offering a comprehensive analysis of the challenges faced by SMEs in evolving economic and environmental landscapes. Its findings carry significant academic importance and practical implications for policymakers, investors, and business leaders in the SME sector.

Chapter 2

Literature Review

2.1 SMEs Financing Choices

Financing poses a formidable challenge for small and medium-sized enterprises (SMEs). The intricate business models and prevailing information asymmetry often lead SMEs to resort to external financing only after exhausting their internal resources (Myers (1984), Berger and Udell (1998)). Berger and Udell (1998) present a "financial growth cycle" model to elucidate the fluctuations in the capital structure as a function of firm age and size. They assert that SMEs, generally smaller and younger, prefer to utilize internal finance and informal external finance before approaching formal financial institutions. Regarding external finance, SMEs frequently encounter difficulties in accessing non-bank financial instruments, particularly those from capital markets (OECD (2017)). Moreover, due to the obscure nature of their business models, SMEs often harbor private information that eludes potential investors. Consequently, banks face challenges in distinguishing SMEs with solid creditworthiness from those with weak credit. In an effort to mitigate potential losses, banks often standardize the credit status of SMEs to determine interest rates or outright deny loan applications (Stiglitz and Weiss (1981)). According to the OECD (2017), a substantial disparity persists between the credit costs of SMEs and large companies. On average, this gap has steadily widened from 2007 to 2016, as evidenced by a 14.9% higher median interest rate charged to SMEs in 2008 and a 56% higher rate in 2015 compared to large corporations.

Berger and Udell (1998) underscore that banks primarily furnish external credit for SMEs, even within advanced economies. Subsequently, Berger and Udell (2002) propose that relationship lending, characterized by the accumulation of "soft" information over an extended lending period, can enhance SMEs' accessibility to external bank financing. In contrast to transaction-based lending strategies, such as financial statement-based, asset-based, or credit scoring-based lending that rely on quantifiable "hard" information, relationship lending employs qualitative data that defy straightforward measurement. Predominantly, SME loans are facilitated by smaller commercial banks. Stein (2002) corroborates this view, emphasizing that these loans largely hinge on longstanding relationships between the banks and the businesses. Similarly, DeYoung et al. (2004) observe that smaller community banks excel in fostering substantial and meaningful relationships with SMEs compared to their larger counterparts. Moreover, Deyoung et al. (2015) explain that these smaller community banks, due to their size, encounter limitations in accessing public market funding, thereby elevating their costs when providing loans to larger firms. This constraint inevitably affects their capacity to offer external financing. However, this necessitates greater autonomy for loan officers, which could potentially amplify agency issues owing to conflicting interests between the bank and its officers, as elucidated by Udell (1989). Therefore, relationship lending may introduce a potential moral hazard.

The financial challenges encountered by SMEs underscore the importance of understanding their capital structure policies. Both theoretical and empirical corporate finance literature have centrally focused on firms' capital structure decisions. Theoretical contributions have been made by Modigliani and Miller (1958), Jensen and Meckling (1976), Miller (1977), and Myers (1984)), while empirical evidence has been provided by Titman and Wessels (1988), Shyam-Sunder and Myers (1999), Fama and French (2002), Lemmon and Zender (2010), and Öztekin (2015). Despite its unrealistic assumptions, Modigliani and Miller (1958) seminal study provides a foundational understanding of a company's leverage choices. They propose that, in a perfect capital market devoid of taxes, transaction costs, bankruptcy costs, and one that provides a homogeneous risk-free rate for both borrowers and lenders, a firm's value remains independent of its capital structure. Modigliani and Miller (1963) refined the M&M theory by incorporating the effects of corporate taxes, thereby emphasizing the tax shield benefits accrued through debt financing. Kraus and Litzenberger (1973) were the first to formally develop the trade-off theory, suggesting an optimal leverage ratio balance between tax shield benefits and bankruptcy costs of debts. However, the empirical evidence does not align with the leverage level predicted by the trade-off theory. As Myers (1984) highlights, given the low risk of large US firms, their debt ratios according to the static trade-off theory prediction are comparatively low. Myers then introduced the pecking order theory to answer the "Capital Structure Puzzle", arguing that due to asymmetric information, external finance often proves costly. As such, firms typically opt to raise external finance only after exhausting internal finance. Consistent with the pecking order theory, firms with more retained earnings typically use less debt. This assertion finds broad support in empirical studies on both large firms and SMEs (Hall et al. (2004), López-Gracia and Sogorb-Mira (2008), Antoniou et al. (2008), D'Amato (2020)).

Jensen and Meckling (1976) and Jensen (1986) agency cost theory underscores the crucial role of ownership structure in determining a firm's capital structure. This theory posits that conflicts of interest between managers and owners can result in suboptimal financing choices. Existing literature primarily explores two facets of the influence of ownership structure on capital structure: ownership concentration (as explored by Fama and Jensen (1983), La Porta et al. (1999), Margaritis and Psillaki (2010), Céspedes et al. (2010), Brailsford et al. (2002), Ellul (2008), Lo et al. (2016)) and the role of the family firm (as per Villalonga and Amit (2006), Anderson et al. (2003), Setia-Atmaja et al. (2009), Schmid (2013),King and Santor (2008), Ellul (2008), and Croci et al. (2011)). These studies predominantly focus on large listed companies, with inconclusive results. In numerous SMEs, owners frequently assume managerial roles, which might mitigate agency conflicts arising from the separation of ownership and control rights (Jensen (1986)). According to the agency cost theory, debt can alleviate friction between managers and shareholders. However, as the debt proportion increases, it can intensify conflicts between shareholders and creditors. Within the SME context, agency costs may appear as disagreements between majority and minority owners or between shareholders and lenders. The impact of ownership concentration and ownership type on capital structure decisions, particularly in the context of SMEs, remains somewhat indeterminate.

In our initial empirical investigation in this thesis, we delve into the relationship between a firm's leverage ratio, risk, and ownership structure, with a particular focus on European SMEs. Through this exploration, we aim to elucidate the complex interaction between ownership structure and capital structure within this critical economic segment. Our goal is to offer insights that can aid both practitioners and policy-makers in fostering the growth and stability of SMEs.

2.2 Overview of Climate Risk

Climate change constitutes one of the most substantial challenges that humanity faces in the 21st century. A multitude of organizations and conferences have been established to address climate risk, such as the Intergovernmental Panel on Climate Change (IPCC), the United Nations Framework Convention on Climate Change (UNFCCC), and the World Wildlife Fund (WWF). Notably, the Paris Agreement (2015) marks a significant step towards global efforts in combating global warming, setting an objective to limit the global temperature increase to 1.5 degrees within this century.

Climate risk bifurcates into two distinct types: transition risks and physical risks. Transition risk pertains to the negative effects stemming from policies designed to curb CO2 emissions. As strategies to transition towards a greener economy gain traction, high-emitting industries like mining and fossil fuel extraction, along with their dependent sectors, could experience significant profit declines (Curtin et al. (2019)). Moreover, Semieniuk et al. (2021) suggest that firms might face transition risks due to technological changes and potential reputational damages as they strive to conform to the emerging low-carbon economic paradigm. Conversely, physical risks are associated with the economic consequences arising from the adverse effects of climate and weather-related events. These risks subdivide further into acute and chronic risks. Acute risks correspond to extreme weather events like floods, droughts, wildfires, hurricanes, and heatwaves, which could inflict considerable damage on hazard-prone areas such as riverbanks or seashores. Chronic risks, on the other hand, relate to gradual climatic changes like temperature increases, sea-level rises, and alterations in precipitation patterns, potentially causing protracted societal transformations (TCFD (2017)).

According to the European Central Bank's 2021 stress test results by Alogoskoufis et al. (2021), physical risk could accelerate at a non-linear rate in the absence of policies promoting a transition towards a greener economy. Additionally, they predict that the primary driver of negative impacts on the banking sector over the next 30 years will be physical risk rather than transition risk.

2.2.1 Global Warming - An Unfolding Reality

The severe repercussions of climate change have been experienced globally by both individuals and corporations. In 2021, Europe and China endured two catastrophic floods. The former impacted Germany, Belgium, Romania, and Italy, leading to over 200 fatalities and resulting in billions of dollars in damage (Cornwall (2021)). The latter, triggered by unprecedented rainfall in Henan Province, caused a reported $16.5 billion in damage and 398 deaths (Zhijian (2023)). Moreover, in July 2022, the United Kingdom witnessed temperatures exceeding 40 °C for the first time since records began (MORIT (2022)), while a concurrent heatwave in Portugal saw temperatures reach a record 47 °C, causing 1,063 deaths within a span of just 11 days (Wikipedia (2023)). In the United States, the 2022 July heatwave affected a fifth of the nation, with temperatures nearing or surpassing 100F (NASA (2022)). There is increasing evidence to suggest that these extreme weather conditions may become the new norm. These events are intrinsically linked to global warming, which results in increased evaporation, leading to higher precipitation and creating inherently unstable warmer air. This leads to intensified rainfall and flash flooding. Thus, it is likely that the events observed in Europe and China will recur with increased frequency as global temperatures continue to rise. It is worth noting that these incidents, which include flash floods in China and Europe, temperatures of 49 °C in Canada, forest wildfires in Australia, and rising sea levels due to polar ice melting, are all occurring at less than 1.5 degrees of average global warming. According to Carleton and Hsiang (2016), the earth's temperature has risen by 0.85 °C compared to pre-industrial revolution levels, and even this marginal increase has led to more frequent extreme weather events with considerable economic and social losses. If carbon emissions are not controlled to achieve the net-zero goal, the global mean temperature is projected to rise by 2 °C since the industrial revolution (Legg (2021)). Consequently, we need collaborative efforts from global governments, like the commitment made at the COP26 Glasgow summit (Hunter et al. (2021)), to reach the net-zero target by the end of the century, thereby managing the trend of global warming. Additionally, individuals and corporations must gain a better understanding of the tangible impacts of global warming. Only through such understanding can we adequately prepare for the implications of a changing climate for businesses.

2.2.2 The Macroeconomic Consequences of Climate Change

Economic literature has extensively studied the effects of climate change. Cross-sectional studies typically reveal a negative relationship between temperature and various measures such as aggregate output, agricultural output, and labor productivity (Dell et al. (2014)). The negative correlation between temperature and per capita income, as noted by Ibn Khaldun in his fourteenth-century work, Muqaddimah, has been recognized for centuries (Gates (1967)). As summarized in Dell et al. (2014), Montesquieu (1989) and Huntington (1924) argue that this negative impact on income arises due to reduced labor productivity under high temperatures. Contemporary cross-country analyses corroborate these findings. Utilizing an international sample from 2000, Dell et al. (2009) identify a strong negative association between the average country temperature and per capita income. They establish that a 1°C increase in temperature leads to an 8.5 percent decline in per capita income, which is a significant decrease. On applying municipal-level data, which allows them to account for country fixed effects, they explored the relationship between temperature and income. While their results continue to be statistically negative, the economic magnitude is considerably less. The drop in per capita income decreases to 1-2 percent (within-country evidence) from 8.5 percent (cross-country evidence).

Utilizing panel data, Hsiang (2010) observes a 2.5% decrease in national output for each 1°C increase in temperature across 28 Caribbean-basin countries. In a similar vein, Dell et al. (2012) report a negative impact of temperature on income in less affluent countries, with little evidence of a similar effect in wealthier nations. With respect to the impact of weather conditions on agricultural output, panel estimates typically demonstrate a negative correlation between unfavorable weather and agricultural productivity in developing countries (Lobell et al. (2011), Guiteras (2009), Welch et al. (2010), Feng et al. (2010)). As for productivity, trustworthy lab experiment results indicate a general productivity loss of 2% for every 1°C increase when the temperature exceeds 25 °C (Seppanen et al. (2003)). Likewise, Graff Zivin and Neidell (2014) find that extreme temperature days, particularly hot ones, reduce activities in outdoor industries.

2.2.3 Corporate Performance in the Era of Climate Risk

The question of whether macro-level weather impacts translate to corporate sectors is a burgeoning area of interest among researchers. Current studies in the realm of climate finance predominantly concentrate on three aspects: market risk, credit risk, and corporate performance.

Regarding market risk, the primary query involves the pricing of climate risk within financial instruments. Bansal et al. (2017) present a theoretical model that embodies a long-term risk perspective, emphasizing temperature-related natural disasters. Their comprehensive model integrates several pivotal elements, including projected temperature trajectories, observed consumption growth, and discount rates derived from both the risk-free rate and equity market returns. Their results suggest that temperature shocks adversely impact asset prices. Balvers et al. (2017), rather than focusing on acute physical risks related to disasters, test the Arbitrage Pricing Theory (APT) model in the U.S. equity market. They ascertain that chronic temperature shocks are a systematic risk factor, which can depress asset prices, with a more pronounced negative effect on industries that are more susceptible to temperature shocks. Employing global data from publicly-traded food companies across 31 countries, Hong et al. (2019) reveal an underreaction of food stock prices to information regarding drought trends. They rank the 31 countries annually based on long-term drought prospects, demonstrating that a lower ranking, indicative of a higher drought risk, can predict weaker stock market returns. They interpret this return predictability as evidence that stock markets may not efficiently incorporate drought-related information.

When considering transition risks, Bolton and Kacperczyk (2021) discern a significant carbon emission premium in U.S. stock returns, even after adjusting for other return predictors, such as company size and book-to-market ratio. The carbon premium observed in their study manifests across all three scopes of emissions. Specifically, they find that a one standard deviation increase in each scope's emission level corresponds to an annualized return increase of 1.8%, 2.9%, and 4.0% respectively.

The investigation of climate change's influence on market risk extends beyond the equity market in the existing literature. An extensive body of research documents the impact of climate risk on corporate bonds, bank loans, municipal bonds, and individual mortgages. Utilizing natural disaster data from SHELDUS, both Correa et al. (2020) and Huang et al. (2022) observe an increased cost of bank loans. With regard to carbon emission risk, Ehlers et al. (2022) dentify a significant carbon premium in global syndicated markets, while Jung et al. (2018) report that high-emission firms face increased debt costs. As the concern over sea level rise (SLR) risk intensifies, properties located near the sea often trade at a considerable discount (Bernstein et al. (2019), Baldauf et al. (2020)). Similarly, Nguyen et al. (2022) identify a SLR premium in long-term mortgages, and Painter (2020) detects the same premium in long-term U.S. municipal bonds.

There is limited existing literature that investigates the translation of climate risk into a company's credit risk, specifically, its default risk. The third empirical study within this thesis explores how chronic physical risk influences the default status of European small and micro firms, measured by the actual default events experienced by these businesses. Numerous studies utilize indirect default measures such as Merton (1974) distance-to-default and Moody's CreditEdge Expected Default Frequency (EDF) as proxies for the default risk of companies. Capasso et al. (2020) spearhead the initial investigation into how climate risk could precipitate a firm's bankruptcy. They found that firms with high scope 1 emissions are more susceptible to default, with credit risk being evaluated through Merton's distance-to-default. Similar findings have been noted in subsequent studies by Nguyen et al. (2023), and Kabir et al. (2021). Through the use of Moody's CreditEdge EDF, Faralli and Ruggiero (2022) determine that carbon risk can negatively affect a firm's default probability via the asset volatility channel. The current body of literature focusing on credit risk studies primarily addresses transition risk in relation to climate change. Our empirical study contributes to the understanding of chronic physical risk. Notably, we find that both rising temperatures and intense precipitation can augment a firm's bankruptcy risk.

Emerging studies are beginning to explore the impact of global warming on corporate performance, though most concentrate on large firms. Addoum et al. (2020) represent one of the initial studies investigating the causal relationship between temperature and a firm's performance, measured by profit and sales revenue. However, they do not find significant results within the context of US markets. As per Dell et al. (2014), rising temperatures have more evident negative impacts on macroeconomic variables in developing countries. Consequently, the absence of an average negative treatment effect of temperature for large US companies is unsurprising, as these entities potentially possess additional resources to diversify climate risk compared to small businesses and firms in developing countries. Subsequent to their initial study, Addoum et al. (2023) shift focus from an average effect to investigate heterogeneous temperature effects across diverse industries. They report that 40% of US industries exhibit heat sensitivity, with both positive and negative effects observed. Using data from 93 countries globally, Pankratz et al. (2023) find that extremely hot days negatively impact a firm's revenue and profit, aligning with Custodio et al. (2022) documentation of a negative impact on sales revenue. Smaller firms are expected to experience more adverse impacts from climate risk compared to larger firms. In the second empirical study of this thesis, we expand the temperature literature on firm performance to include small and medium-sized enterprises and introduce the Eurozone market to scholarly discussion.

Chapter 3

The relationship between SMEs' leverage, risk and ownership

3.1 Introduction

Since the seminal work of Modigliani and Miller (1958), a large literature has focused on how firms determine their capital structure. Several theories have subsequently emerged, including the trade-off theory by Miller (1977), the pecking order theory by Myers (1984), and the agency cost theory by Jensen and Jensen and Meckling (1976). These foundational theories underpin subsequent empirical studies on capital structure. The trade-off theory posits an optimal leverage ratio that maximizes debt tax shields while minimizing bankruptcy costs. Conversely, the pecking order theory proposes that firms favor internal over external financing, and debt over equity when they must resort to external funding. The agency cost theory suggests that the blend of debt and equity depends on the interactions and objectives of a firm's managers, debt-holders, and equity holders.

However, much of the empirical research on capital structure has centered on large firms, with few focusing on small and medium enterprises (SMEs). Nonetheless, SMEs represent crucial economic entities in both developed and developing countries. For instance, nearly 99.8% of the non-financial business sector (NFBS) in the EU-27 comprises SMEs. These enterprises significantly contribute to the economy by providing 70% of new jobs and contributing to over half of the EU's GDP (Muller et al. (2015)).

This paper primarily aims to investigate the relationship between SMEs' leverage and both the ownership concentration and the characteristics of the ultimate owner. The ownership concentration measure we use is based on the percentage of equity capital owned by the largest shareholder (Margaritis and Psillaki (2010)). We categorize the ultimate owner, defined as the entity or individual who directly or indirectly controls the firm, into one of the following Orbis categories: financials, industrials, families, or government. We propose that when controlling firms operate within the same industry as the controlled firms, the former are less risk-averse and permit the latter to leverage more.

This paper contributes to existing literature in three significant ways. Firstly, to our knowledge, our study is the first to encompass the majority of the Eurozone economy, placing particular emphasis on small and medium enterprises (SMEs). Previous work, such as Hall et al. (2004), studied the determinants of the capital structure of SMEs in eight European countries. However, their cross-sectional data utilized only a single year (1995), and the total number of firms studied was 3,951. Likewise, Mac an Bhaird and Lucey (2010) examined a sample of 299 Irish SMEs, finding age, size, asset tangibility, ownership structure, and collateral provision to be key determinants of capital structure. López-Gracia and Sogorb-Mira (2008) tested whether trade-off and pecking order theories can explain the financing choices of 3,569 Spanish SMEs from 1995 to 2004. They posited that these theoretical models, built on large corporations, can help elucidate SME capital structure. More recent evidence from D'Amato (2020) showed that the global financial crisis negatively impacted the leverage ratio of 14,500 Italian SMEs between 2006 and 2016. The authors found the negative impact to be more pronounced among short-term debt than long-term debt. Utilizing comprehensive data across 75 countries from 2004-2011, Demirgüç-Kunt et al. (2020) observed a universal deleveraging trend after the 2008 financial crisis, most pronounced in non-listed companies (including both SMEs and large non-listed companies). Even though they used a large sample dataset covering 276,998 global firms, micro firms were excluded from their study. Contrary to the static model used previously, Daskalakis et al. (2017) employed a dynamic partial adjustment model to gauge how rapidly Greek SMEs adjusted their capital structure to an optimal target under varying macroeconomic conditions. They determined that firm-specific factors were more crucial during growth periods, whereas macroeconomic factors gained importance during recession periods. Unlike previous studies, our research does not confine the analysis to a specific European country but includes both large firms and SMEs (including micro firms) across 12 European countries. Our dataset comprises 625,483 companies (96% of which are SMEs), making it the largest dataset used for studying the capital structure of European companies. Consequently, we are more confident in generalizing our findings within the context of the Eurozone economy, compared to previous studies.

Secondly, we extend the relatively sparse literature examining how a firm's ownership structure influences its financing choices. Specifically, we confirm an inverted U-shaped relationship between ownership concentration and capital structure, as measured by three different definitions. This relationship was initially documented in the work of Brailsford et al. (2002), where they identified a nonlinear, inverted U-shaped relationship between leverage ratio and managerial share ownership for 216 Australian listed companies. Conversely, they discovered a positive relationship for equity ownership among blockholders. Drawing on a sample of 112 listed French firms from 1998-2009, de La Bruslerie and Latrous (2012) found that controlling shareholders tend to increase their share in the capital through borrowing when they have a minor stake in a company. However, upon reaching a certain level of ownership (typically around 40%), these shareholders tend to reduce the firm's leverage ratio to minimize the risk of financial distress. This non-linear, inverted U-shape relationship between controlling rights concentration and leverage ratio was also observed in Taiwanese publicly listed companies (Lo et al. (2016)). In contrast, Céspedes et al. (2010) found a negative relationship between ownership concentration and debt ratio when the ownership concentration was low, and a positive relationship when high, based on a sample of 806 Latin American firms from 1996 to 2005. Due to the scarcity of ownership data compared to other accounting data, previous non-linear ownership concentration effects based on small samples may not be representative and challenging to generalize. Our study, backed by more comprehensive data, confirms that the non-linear ownership concentration finding documented for large firms also applies to SMEs.

Additionally, our research is the first to explore how various categories of ultimate owners can impact a firm's capital structure decisions. Prior studies have only distinguished between family and non-family firms, and their empirical findings regarding the relationship between family ownership and debt ratio have been inconsistent. Research indicating no significant differences in debt ratios between family and non-family firms includes Anderson et al. (2003) analysis of US companies. Negative correlations have been identified in studies conducted in France and Germany; Margaritis and Psillaki (2010) reported that French family businesses use less debt compared to non-family ones, while Ampenberger et al.

(2013) and Schmid (2013) found similar results for German firms, suggesting they tend to avoid debt. On the other hand, positive correlations between family ownership and higher debt ratios have been observed in studies in Australia, Canada, and multinational investigations. Setia-Atmaja et al. (2009) observed that Australian family firms use more debt than their non-family counterparts, a result echoed in King and Santor (2008) Canadian study. Moreover, Ellul (2008) and Croci et al. (2011), in their transnational studies, indicated a positive link between family ownership and leverage ratio. In our paper, we categorize firms into dispersed firms (without a global ultimate owner), family-controlled firms, industry companies-controlled firms, financial companies-controlled firms, and government-controlled firms. We find family firms typically use the most debt and government firms use the least. The total debt to total capital ratio of family firms is 16.7 percentage points higher than that of government firms. In our robustness test, we also demonstrate that firms tend to use more debt when they are in the same industry as their ultimate owner, and they are also likely to mimic the capital structure of their ultimate owner.

Thirdly, our research doesn't limit itself to a singular measure of capital structure. Instead, we evaluate how firm-specific determinants impact several commonly adopted measures of leverage. We demonstrate that the influence of firm-specific determinants can differ across different measures, particularly when transitioning from the 'total debt to total capital' measure to the 'total liabilities to total assets' measure. Welch (2011) was the first to discuss this issue in capital structure research, advocating against the use of leverage defined by financial debt over total assets, as it equates non-financial liabilities with equity. Rajan and Zingales (1995) suggest that the ratio of total liabilities to total assets might overstate leverage and propose that the ratio of total debt to total capital, where capital is the aggregate of debt and equity, serves as a superior indicator of past financing decisions. We also examine how a firm's risk profile influences its financing choices. Incorporating risk measures into an SME study is demanding, as the risk proxy construction (measured by the three-year rolling volatility of profit) often discards numerous observations. As an alternative, D'Amato (2020) employs the absolute difference between the annual profit and the mean of annual profits for a specific firm to gauge firm risk. However, this risk measurement proposed by D'Amato (2020) might induce endogeneity issues as it includes the mean value of future annual profits.

In addressing the concerns regarding the external validity of the analysis due to the chosen sample period from 2007 to 2014, it's essential to contextualize the European economic landscape during these years. This period, marked predominantly by the aftermath of the global financial crisis, was characterized by economic instability and tightening market conditions, particularly in Europe. The general financial crisis led to a significant contraction in credit markets, posing challenges for businesses, especially SMEs, in raising capital. This backdrop provides a unique setting to examine how SMEs navigate capital raising in constrained financial environments, offering insights into their resilience and adaptability.

However, it is crucial to acknowledge the limitations of this sample period. The economic turmoil and the subsequent policy responses, including stringent banking regulations and monetary easing by central banks, were not typical of regular market conditions. Therefore, the findings of this study, while highly relevant to understanding SME behavior during economic downturns, may not fully extrapolate to periods of economic stability or growth. The atypical market dynamics during this crisis period could influence SMEs' capital structure decisions in ways that are not representative of their strategies in more stable times. This limitation underscores the need for a cautious interpretation of the results and suggests potential avenues for future research in different economic cycles to validate and complement the findings of this study.

The remainder of this paper is structured as follows: Section 2 reviews previous studies investigating the determinants of capital structure. Section 3 describes the data, while Section 4 outlines the methodology. Section 5 and Section 6 discuss the baseline empirical results and robustness tests, respectively. Finally, Section 7 concludes the paper.

3.2 Determinants of the capital structure

Capital structure decisions are typically determined by two types of explanatory variables according to researchers: firm-specific variables proposed by the pecking order and trade-off theory(Hall et al. (2004), López-Gracia and Sogorb-Mira (2008), Antoniou et al. (2008), Mac an Bhaird and Lucey (2010),Daskalakis et al. (2017), and D'Amato (2020)) and macro variables (Mokhova and Zinecker (2014), Daskalakis et al. (2017)). Empirical results from these studies indicate that factors such as firm size, profitability, asset tangibility, growth opportunities, and firm age significantly impact leverage among accounting ratios. However, these relationships are not consistently directed. Trade-off theory suggests a positive correlation between profitability and the debt ratio, as less risky firms are likely to use more debt to maximize profits (Dammon and Senbet (1988)). Contrarily, Myers (1984) introduced the pecking-order theory to address the capital structure puzzle, explaining why US corporations generally exhibit lower risk and leverage ratios than predicted by the trade-off theory. According to the pecking order theory, a profitable firm primarily uses internal finance for new investments before resorting to external finance, resulting in a negative relationship between profitability and leverage ratio. This theory is widely supported by empirical evidence (Hall et al. (2004), López-Gracia and Sogorb-Mira (2008), Antoniou et al. (2008), D'Amato (2020) etc.). Larger firms, due to their diversification and more stable profits, face lower default risk compared to SMEs (Rajan and Zingales

(1995)). Conversely, SMEs often encounter financing issues due to their opaque business models and information asymmetry. Thus, size can be used as a proxy for risk and information asymmetry and is expected to correlate positively with the leverage ratio. Empirical results largely validate this prediction (López-Gracia and Sogorb-Mira (2008), D'Amato (2020), Antoniou et al. (2008), Mc Namara et al. (2017)). Asset tangibility, measured as the ratio of tangible assets to total assets, could be positively related to the debt ratio, as tangible assets can serve as collateral when SMEs apply for loans (Harris and Raviv (1990)). Alternatively, it might be negatively associated with the debt ratio, as tangible assets reduce information asymmetry, thus lowering the cost of equity issuance (Frank and Goyal (2003)). The age of a firm can positively or negatively influence capital structure. Older firms, with lower bankruptcy risk, are predicted by the trade-off theory to prefer higher leverage ratios (Kieschnick and Moussawi (2018)). On the other hand, older firms will have more accrued earnings and tend to have a lower debt ratio (López-Gracia and Sogorb-Mira (2008), D'Amato (2020)).

Recent research suggests that macro-environmental conditions and a country's institutional environment play significant roles in determining capital structure. For instance, Mc Namara et al. (2017) demonstrated that Small and Medium Enterprises (SMEs) exhibit higher borrowing tendencies in European countries with effective bankruptcy laws and comparatively lower bank regulatory capital. D'Amato (2020) highlighted a substantial decrease in short-term leverage for

SMEs following the financial crisis. Furthermore, a comprehensive data analysis across 75 countries by Demirgüç-Kunt et al. (2020) revealed pronounced deleveraging amongst SMEs and non-listed firms during the global financial crisis. Recently, Alter and Elekdag (2020) examines the relationship between US shadow rates and the change in leverage ratio in 28 emerging markets. They point out that the improving global financial condition can stimulate the increase of the debt ratio in emerging markets.

Another line of research aligns with the trade-off theory, typically focusing on the adjustment speed of the leverage ratio using a partial adjustment model. Daskalakis et al. (2017) discovered that the long-term debt adjustment speed of SMEs slows down under deteriorating macroeconomic conditions, with no apparent change in short-term adjustment speed. They also found that macroeconomic determinants carry more weight in crisis conditions when comparing their explanatory power to firm accounting ratios. According to their findings, SME managers often find it challenging to modify leverage during unfavorable periods.

The aforementioned studies underscore the significance of firm-specific attributes, banking regulation, and macroeconomic conditions in determining a firm's capital structure. However, ultimate financing decisions are made by the firm's manager. The agency cost theory implies that conflicts of interest between managers and firm ownership can impact a firm's performance and its capital structure. Regrettably, only a handful of existing research focuses on the role of ownership in capital structure decisions, with even fewer exploring the influence of SME ownership on financing decisions. Margaritis and Psillaki (2010) probed the correlation between firm performance, capital structure, and ownership structure. Utilizing a non-parametric method and quantile regressions, they examined whether ownership concentration and ownership type impact French firms' performance and debt ratios. A small sample from Bureau van Dijk was collected, and ownership concentration was measured based on the percentage of shares held by the largest shareholder. According to their findings, firms with concentrated ownership tend to use more debt. However, the influence of ownership type on leverage did not yield significant results. Céspedes et al. (2010) studied the relationship between ownership and capital structure in Latin America. Despite facing higher financial distress risk and receiving fewer tax benefits than U.S. firms, Latin American firms' overall leverage level is not less. In addition to traditional capital structure determinants, the authors posit that ownership concentration significantly influences firms' leverage choices. They measured ownership concentration using the Herfindahl index, constructed from the largest ten shareholders. Employing a sample of 1,168 large firms, they identified a positive relationship between ownership concentration and the leverage ratio. They contend that, due to the high level of ownership concentration in Latin American firms, the value of control surpasses that of dispersed firms. When confronted with new investment decisions, such firms are likely to issue less equity to safeguard their existing control rights, leading to a positive relationship between debt ratio and ownership concentration.

However, the correlation between ownership concentration and leverage ratio may not be linear. Firms with dispersed ownership are more prone to Type 1 agency costs, signifying a conflict of interest between managers and shareholders. In these instances, shareholders' control rights are too feeble to efficiently monitor managers, who are more likely to utilize the firm's resources to advance their own objectives against shareholders' interests. Jensen (1986) "Free Cash Flow Theory" posits that debt can mitigate this conflict. Managers, compelled to use the firm's free cash flow for interest payments, are deterred from squandering it on inefficient investments. Consequently, a lower level of ownership concentration could result in a higher debt ratio. As ownership concentration increases, shareholders can more readily exert their control power over the company, influencing managerial behavior. In this context, the role of debt as a monitoring instrument may not be as significant as in dispersed firms. Moreover, the controlling shareholder, often heavily invested in a single firm and relatively undiversified, might prioritize bankruptcy risk. Therefore, firms with concentrated ownership are inclined to reduce their debt ratio to mitigate bankruptcy risk. Several studies, including Brailsford et al. (2002), Ellul (2008), and de La Bruslerie and Latrous (2012), have identified an inverted U-shaped relationship between ownership and capital structure. Brailsford et al. (2002) found an inverse U-shaped relationship between managerial ownership and leverage, and a positive correlation between external block ownership and leverage. Utilizing the percentage of board directors controlled by the ultimate owner as a concentration proxy, Lo et al. (2016) reported a non-linear relationship between controlling rights' concentration and leverage in Taiwanese companies. This inverse U-shaped relationship is more robust when ownership concentration is proxied by the ownership of the top five shareholders. They also found that family-controlled firms have a 6.2% higher debt ratio than non-family-controlled firms and that family control moderates the link between ownership concentration and leverage.

3.3 Data and summary statistics

The original sample data, amassed from Orbis Bureau van Dijk, encompass approximately 20 million firm-year observations prior to 2015 in Europe. However, observations from 2005 onwards are retained due to the limited data coverage before this year. Following the approach of traditional corporate finance literature (Cathcart et al. (2020)), firms operating in public or financial sectors are excluded. Unreliable observations such as firms with negative asset or liability values are also discarded, along with observations missing dependent variables or specific explanatory variables. Countries with fewer than 1,000 total firm-year observations are also eliminated from the dataset. Following this initial stage of data cleaning, the dataset is reduced to approximately 6.2 million firm-year observations.

Given our primary focus is to investigate how ownership structure and firm risk influence leverage, only observations with risk and ownership data are retained. Observations from 2005 and 2006 are removed when constructing the three-year rolling volatility of firm risk. Upon the completion of this secondary data filtering stage, the final sample consists of 3.67 million observations spanning from 2007 to 2014.

For comparison, Demirgüç-Kunt et al. (2020) also sourced their global data from Orbis. However, our sample's coverage of the European continent considerably surpasses that of Demirgüç-Kunt et al. (2020). Notably, we did not exclude micro firms from our study, in contrast to Demirgüç-Kunt et al. (2020), who only included medium and small firms. Demirgüç-Kunt et al. (2020) acknowledged that their global data study could not avoid survivorship bias. In contrast, our vintage data procured directly from Orbis encompasses both historically active and inactive firms. Illustrating the difference in sample coverage, Demirgüç-Kunt et al. (2020) accounted for approximately 35,000 firms in Italy from 2004 to 2011, while our final data set for regression analysis covers 198,185 Italian firms from 2007 to 2014.

Table 3.1 presents the summary statistics of the sample. It reveals an average total liability-to-asset ratio of 0.673, indicating that firms tend to rely more on short-term liabilities (0.5) than long-term liabilities (0.16). Approximately 95%

of the observations in our sample represent SMEs, with total assets less than 43 million euros. As for the financial debt ratio, the distinction between long-term and short-term is not as pronounced as with the total liability-to-asset ratio. A notable finding is the significant use of trade credit by European SMEs, accounting for 30% of their total liabilities and 20% of their total assets.

Table 3.2 outlines the variety of leverage ratios and SME categorizations by country. The sample includes 12 European countries, with the United Kingdom excluded due to most UK firms lacking sales data in the Orbis database. Italy and France constitute over half the sample (56.77%). Of the 12 countries, Italy has the highest total liability-to-asset ratio (73.84%). However, when defining the leverage ratio as total debt over total capital, Portugal records the highest leverage (47.36%). Comparing the ratio between the third and fourth columns reveals that firms in Belgium, France, Italy, and Norway rely more heavily on trade credit than debt financing, a trend reversed for firms in Switzerland, Germany, Spain, Finland, Greece, Netherlands, Portugal, and Sweden. This table underscores the necessity of controlling country fixed effects in the regression analysis.

Table 3.3 presents the categorization of firm ownership concentration as provided by Orbis. Firms are distinguished into four indicators based on the total or direct shareholding of the largest shareholder. 'A' represents firms with less than 25% of shares owned by the largest shareholder; 'B' corresponds to firms where the largest shareholder owns between 25% and 50% of the shares; 'C' and

'D' are assigned to firms where the majority shareholding exceeds 50%. The key distinction is that 'D' denotes direct shareholding while 'C' indicates total shareholding, both direct and indirect. For subsequent analysis, we amalgamate 'C' and 'D' categories. Observations reveal a tendency towards a concentrated ownership structure, with 67.27% of the firm-year observations possessing an owner controlling more than 50% of the rights. Only 5.77% of the firm-year observations display a dispersed ownership structure (category 'A').

In table 3.4 we provide the average value of various leverage ratios and firm characteristics, sorted according to the degree of their ownership concentration. A clear escalation is observed in the total liability-to-asset ratio as firm ownership concentration shifts from Category A to Category B. Firms with moderate ownership concentration (Category B) tend to exhibit the highest short-term debt ratio and trade credit ratio, as demonstrated by SD/TA, SD/TC, and Trade/TA. The data also reveals that younger, riskier firms are inclined towards higher ownership concentration. Furthermore, a higher ownership concentration correlates with greater profitability and growth, along with a lower tangibility ratio.

3.4 Methodology

To investigate the influence of ownership concentration and firm risk on the capital structure of SMEs, we apply pooled OLS regressions.

$$Leverage_{i,t} = \alpha + \beta X_{i,t} + \gamma Ownc_i + \delta Ownc_i^2 + \rho Risk_{it} + \theta_c + \theta_j + \theta_t + \epsilon_{it} \quad (3.1)$$

Equation 3.1 serves as our baseline model, where i and t denote the indices for firm and year respectively. The firm-year leverage ratio is regressed on an intercept, firm-specific controls $X_{i,t}$, a proxy of ownership concentration $Ownc_i$, and its squared term $Ownc_i^2$ to account for a potential non-linear relationship. In addition, a proxy for firm risk $Risk_{it}$ is included. We also account for country, industry, and year fixed effects, indicated by $\theta_c, \theta_j, \theta_t$. One of this study's limitations is the inability to control for firm fixed effects in the regression model, given that our ownership concentration measure is time-invariant.

$$Leverage_{i,t} = \alpha + \beta X_{i,t} + \gamma GUO_i + \delta Risk_{it} + \theta_c + \theta_j + \theta_t + \epsilon_{it} \quad (3.2)$$

Equation 3.2 is utilized to explore the impacts of different types of global ultimate owners (GUO). To avoid the issue of multicollinearity when examining the impacts of the ultimate owner, the ownership concentration measure $Ownc_i$ is not included in the equation. According to Orbis, firms with an ultimate owner typically exhibit a high-concentration ownership structure since the ultimate owner directly or indirectly controls over 50% of the shares of the controlled firms. As in previous models, we account for country, industry, and year fixed effects. For all regression models, we report White (1980) heteroskedasticity-robust standard errors clustered at the firm level.

3.4.1 Measures of leverage

We use three different measures of leverage in the following regressions.

1. **TL/TA**: This measure denotes the ratio of total liabilities to total assets, which is frequently used in empirical studies, especially those focusing on SMEs, due to its availability. However, it is important to note that total liabilities also incorporate non-financial liabilities such as trade payable, pension liabilities, provisions, and deferred taxes. Consequently, it might exaggerate the firm's financing needs with respect to the banking sector and financial markets.

2. **TD/TA**: This ratio signifies the total debt to total assets. Total debt comprises long-term financial debt (including loans from credit institutions and bonds) and short-term loans (incorporating long-term debt with less than one year's maturity). By disregarding non-financial liabilities in the numerator, this measure might underestimate the total leverage ratio.

3. **TD/TC**: This measure, representing the total debt to total capital, more

accurately reflects a firm's requirements for external financing. Total capital is defined here as the sum of shareholder equity and total debt.

Empirical SME studies often conflate the definition of liability ratio and debt ratio. For instance, D'Amato (2020) asserts that they utilize the debt to total assets ratio (D/TA) to measure leverage. However, upon closely comparing their summary statistics with ours, we ascertain that their D/TA ratio is actually representative of the total liability to total assets ratio. Conversely, Daskalakis et al. (2017) explicitly state that their measurement of debt ratios refers to "the book value of interest-bearing debt over total assets". Demirgüç-Kunt et al. (2020) also highlights they focus on a narrow definition of total financial debt ratio. Our extensive European SME data allows us a sizable sample even when employing all three measures. Furthermore, we decompose each measure into long-term and short-term leverage, and for the second measure, we additionally examine the trade credit component.

3.4.2 Firm specific determinants

- **Size** is the natural logarithm of total assets. Size can be regarded as an inverse proxy of the default risk or a proxy of information asymmetry. In empirical studies, we often observe a positive effect on capital structure (López-Gracia and Sogorb-Mira (2008), D'Amato (2020), Antoniou et al. (2008), Mc Namara et al. (2017)).

- **Age** is calculated as the natural log of a firm's lifespan (from inception to the present). While Kieschnick and Moussawi (2018) define age differently for public firms—measuring the duration since the firm's initial public offering—they discovered a negative correlation between age and the extent of debt used. Generally, as firms age, they accumulate more earnings, reducing their need for debt financing. Simultaneously, they observed a positive correlation between age and the likelihood of using debt financing.

- **Profitability**, determined as pre-tax return on assets (ROA), can impact leverage positively according to trade-off theory, while pecking order theory suggests a negative effect. Empirical evidence often supports the pecking order theory (Hall et al. (2004), López-Gracia and Sogorb-Mira (2008), Antoniou et al. (2008), D'Amato (2020) etc.)

- **Tangibility** is calculated as the ratio of tangible assets to total assets. Firms with a high proportion of tangible assets tend to incur lower bankruptcy costs. Additionally, tangible assets can serve as collateral for debt financing, implying an anticipated positive effect.

- **Sale growth**, defined as the annual return on sales, is a widely-used proxy for growth opportunities in prior research(Hall et al. (2004); López-Gracia and Sogorb-Mira (2008); Palacín-Sánchez et al. (2013); Daskalakis et al. (2017)). Another growth indicator is the ratio of total sales to total assets. Myers (2001) argues that high-growth firms have more at stake in a debt-overhang situation, causing them to rely more on equity than debt. Conversely, some studies find that robust sales can support greater debt financing.

- **Risk** is quantified as the three-year (including the current year) rolling volatility of *Profitability*. Trade-off theory primarily predicts a negative effect of risk on capital structure. Although cash flow or asset volatility is often used to measure risk in empirical studies, data limitations for SMEs lead some researchers to use the absolute difference between the profitability in year t and the average profitability over the sample period as a risk proxy (Antoniou et al. (2008), Deesomsak et al. (2004), D'Amato (2020)). This risk proxy, however, uses future profitability values, complicating causality inference.

3.4.3 Measures of ownership concentration

Two distinct measures are utilized to capture the degree of ownership concentration:

1. **Direct Shareholding** serves as the principal proxy for $Ownc_i$ in equation 3.1. We include both *Direct Shareholding* and its squared value to accommodate the nonlinear relationship between ownership concentration and firm leverage.

2. **Ownership concentration** is the factor variable presented in Table 3.3.

As clarified in the summary statistics, Orbis assigns an ownership concentration indicator to most firms, thereby defining their level of ownership concentration. 'A' symbolizes firms with the least concentration, while 'C' represents those with the highest. It's essential to understand that $Ownership\, concentration$ cannot be straightforwardly derived from $Direct\, Shareholding$. This measure classifies firms into various levels of ownership concentration, considering both direct and total shareholding. The outcomes using the factor variable $Ownership\, concentration$ will be revealed in the robustness tests.

3.4.4 Global ultimate owner (GUO)

BvD designates its GUO (Global Ultimate Owner) as the shareholder with the most significant direct or total ownership. Researchers may use either a 25.01% or 50.01% threshold at each step of the UO (Ultimate Owner) selection process. For this paper, we adopt a 50.01% threshold to define the global ultimate owner. Consequently, firms assigned an indicator 'C' are those with an ultimate owner. This approach ensures the ultimate owner identified in our sample truly exercises control over the subject firms. It is important to note that a firm will automatically be its own GUO in the Orbis database if it is the GUO of its corporate group, regardless of its relative independence (i.e., with indicator 'A' or 'B'). We adjust for this by treating these firms as if they lack a GUO, ensuring the GUO differs from the firm itself.

Apart from determining whether a firm has a GUO, BvD also offers information on the type of GUO. Adapting the approach of Kalemli-Ozcan et al. (2015), we classify GUO types into five categories: firms without a GUO, firms with an Industry company GUO type, Individuals or families GUO type, Financial GUO type, and Government GUO type respectively. Figure presents the distribution of sample observations by different GUO types. As illustrated, 32.73% of our sample observations lack an ultimate owner, while 39.15% have individuals or families as their GUO. The second most prevalent GUO type (20.57%) is the industry company, where the firm is controlled by another dispersed company (a company without an ultimate owner). Financial type and government type account for 6.18% and 1.37% respectively.

3.5 Results

3.5.1 The impact of risk and ownership concentration

Our baseline model Equation 3.1 is estimated across ten distinct specifications. The first three regressions utilize the ratio of liabilities to total assets as dependent variables. The subsequent four regressions incorporate the ratio of financial debts, as well as trade credit to total assets, as dependent variables. In the final three regressions, we employ the ratios of debts to total capital as dependent variables. For all ten specifications, we regress various leverage ratios on firm-specific determinants in conjunction with the first and quadratic term of the largest shareholder's direct shareholding.

Table 3.5 presents the regression results. Notably, both $Profitability$ and Age consistently exert negative impacts on leverage across all specifications, with a significance level at 1%. This negative correlation between profitability and leverage ratio aligns with the Pecking Order Theory. This theory posits that due to information asymmetry between external investors and firms, which is commonly observed in SMEs, more profitable SMEs tend to finance new investments with their retained earnings. Consequently, a more profitable firm with ample retained earnings will resort less to borrowing.

Upon examining regressions 5-6 and 9-10 in greater detail, no significant distinction emerges between the impacts of profitability on long-term and short-term debt. However, profitability exerts a more negative effect on the current liabilities ratio compared to the non-current liabilities ratio (-0.445 for SL/TA vs -0.253 for LL/TA). As for the influence of age, the leverage ratio tends to decrease as the firm matures. Furthermore, age appears to affect the long-term debt ratio (LD/TA and LD/TC) more significantly than the short-term debt ratio (SD/TA and SD/TC). The recent study of D'Amato (2020) corroborates these findings. Nonetheless, examining a considerably smaller Italian SME sample, D'Amato (2020) observes a more pronounced negative impact of age on short-term leverage, with no significant impact on long-term leverage. Interestingly, our regression results for columns 2 (LL/TA) and 3 (SL/TA) endorse the more negative impact on short-term leverage. As previously noted, D'Amato (2020) debt ratio is, in fact, the liability ratio, underscoring the need to distinguish various measures of leverage ratios in capital structure studies. Given that the liabilities ratio incorporates a non-debt leverage component, divergent conclusions between the liability ratio and the debt ratio should not be surprising. In accordance with our results, a study of Irish SMEs by Mac an Bhaird and Lucey (2010) reveals that the usage of long-term debt is negatively associated with firm age. In their view, firms accumulate more retained earnings and decrease debt usage to finance new investments as they mature, indicating a maturity matching.

The coefficients for *Tangibility* underscore the necessity of distinct discussions for long-term and short-term leverage. Evident from our results, asset tangibility positively impacts firms' long-term leverage ratio (both liability and debt ratios), while it inversely affects their short-term leverage ratio (inclusive of liability, debt ratios, and the trade credit ratio). The overall influence of tangibility on the financial debt ratio is positive, with significant positive coefficients of 0.215 for TD/TA and 0.207 for TD/TC. These outcomes suggest that SMEs with more tangible assets are inclined to substitute riskier short-term loans with safer long-term debt. As these tangible assets can serve as collateral, SMEs gain easier access to long-term loans from banks. If able to borrow long-term finance, SMEs will avoid short-term loans, thereby circumventing the recurring risk each time a short-term loan matures.

The effect of firm size on the financial debt ratio is positive, a finding that aligns with most empirical studies. However, our study reveals that smaller firms rely more heavily on trade credit financing (-0.014 on $Trade/TA$), a finding that is not unexpected. As demonstrated in Table 1, trade credit is the predominant financing source in our sample, particularly for SMEs. For these smaller firms, the financial threshold for trade credit is likely lower than for debt financing, leading to greater utilization of trade credit. This is consistent with Carbo-Valverde et al. (2016), who found that smaller, constrained SMEs tend to rely more heavily on trade credit than on bank loans. We contend that the negative size effect on the current liability ratio (-0.024 in SL/TA) is partially attributed to trade credit and other non-debt leverage components.

With respect to the coefficient of $Growth$, firms exhibiting higher growth opportunities tend to utilize more debt financing, particularly long-term debt, as their internal resources may be insufficient to support such rapid growth. Similar findings have been noted in earlier studies on SMEs(Margaritis and Psillaki (2010); D'Amato (2020)). However, this result contradicts the agency cost theory's prediction. As Myers (2001) argues, growth firms with high debt ratios stand to lose more in the event of escalating conflicts between shareholders and debt holders, exacerbating the underinvestment issue. According to Myers

(2001), growth firms typically depend more on equity financing and maintain a lower leverage ratio. Mc Namara et al. (2017) discovered that growth is negatively associated with long-term debt ratio, while it is positively related to the short-term ratio. Brailsford et al. (2002) also reported a significant negative impact of growth opportunity on the debt to equity ratio.

Our analysis of the firm risk effect generally supports the predictions of the trade-off theory: firms tend to borrow less when bankruptcy risk increases. An exception is the positive risk effect on SL/TA; riskier firms usually have significantly higher short-term liabilities. This result warrants careful interpretation. It does not necessarily imply that riskier firms borrow more. As we previously clarified, the current liability ratio includes non-debt and non-trade credit leverage components. Hence, the positive effect of risk on SL/TA might merely reflect changes in other non-financial current liabilities, such as pensions, personnel costs, taxes, intragroup debts, advanced account receipts, among others (as per the Orbis definition). For instance, as a firm becomes riskier, it may accrue more deferred tax or wages payable. Concerning external finance-related leverage ratios (specifications 4-10), our results align with theoretical predictions. The results for the financial debt ratio and trade credit ratio demonstrate that riskier firms indeed borrow less from creditors and suppliers. Studies on the impact of firm risk on SMEs' capital structure are scarce due to the complexity of constructing risk proxies like asset volatility, which requires comprehensive data over successive years—an issue often faced when handling SME data as it may not provide consistent profitability values over a span of 3 or 5 years. Studies on SMEs often tend to focus on how macro-environment risk impacts their capital structure, rather than the firm's intrinsic risk. For example, Daskalakis et al. (2017) found that the adjustment speed for the long-term debt ratio slows down during crises, and Demirgüç-Kunt et al. (2020) noted a significant deleveraging and maturity reduction trend since the global financial crisis.

Transitioning to our primary research focus, we aim to examine the influence of ownership concentration on a firm's leverage selection. We utilize the percentage of the firm's largest shareholder's direct shareholding as a proxy for the ownership concentration level. Our findings reveal that Direct Shareholding positively impacts both the total liability (TL/TA) and current liability ratios (SL/TA). This effect is non-linear, as both coefficients for the quadratic term are significantly positive. A positive linear relationship also exists between ownership concentration and the trade credit ratio at a 5% level. Nonetheless, considering our extensive observations in the $Trade/TA$ specification (3.65 million), this does not provide robust evidence of ownership's impact on trade credit. Our results suggest that firms increase their total liabilities ratio, current liabilities ratio, and trade credit ratio as they become more ownership-concentrated. Céspedes et al. (2010) contend that firms will favor debt financing if issuing equity implies a control sharing. For highly concentrated SMEs—which is predominantly the case in our sample, as Table 3.3 indicates that 94.23% of our sample includes an owner with more than 25% shares in that firm—control rights hold significant value to the owners. Owing to their opaque business models, SMEs experience asymmetric information problems. Moreover, compared to firms controlled by diversified shareholders, these issues are more severe for SMEs controlled by a single large shareholder. Equity issuance is particularly costly for these firms. Consequently, we observe a positive relationship between ownership concentration and the leverage ratio.

With respect to the debt-related leverage ratio (specifications 4-6 and 8-10) and the long-term liability ratio (specification 2), our analysis identifies a reversed U-shaped relationship between ownership concentration and the respective leverage ratios. Initially, as the direct shareholding of the largest shareholder increases, the financial debt ratio also escalates. However, when the ownership structure becomes excessively concentrated, firms begin to diminish their financial debt ratio. This finding aligns with the non-linear correlation identified between ownership concentration and capital structure, as indicated in studies by Brailsford et al. (2002), Lo et al. (2016), Ellul (2008), and de La Bruslerie and Latrous (2012). According to the free cash flow theory, debt financing can moderate the conflicts between managers and shareholders. At lower levels of ownership concentration, debt is employed as a monitoring tool to avert the over-investment problem and potential expropriation of the firm's free cash by managers. As a firm becomes more ownership-concentrated and consequently more risk-averse, the fear of bankruptcy risk supersedes the benefits of using debt. Thus, firms with higher ownership concentration reduce their debt ratio, leading to a reversed U-shaped relationship between ownership concentration and leverage ratio. The turning point of the ownership concentration level can be computed using the formula $-\frac{b}{2a}$, where b is the coefficient of $OWN\,Concentration$ and a is the coefficient of $OWN\,Concentration^2$. All other things being equal, the LL/TA and LD/TD ratios reach their apex when the direct shareholding is 50%. Meanwhile, the TD/TA, SD/TA, TD/TC, LD/TC, and SD/TC ratios attain their highest values at direct shareholding levels of 54.7%, 57.0%, 63.3%, 59.8%, and 64.7%, respectively.

Difference between "good" volatility and "bad" volatility

In the preceding section, we utilized the volatility of profitability over the previous three years as a proxy for firm risk. However, volatility is merely a representation of risk and, in certain instances, may denote its inverse. Consider two scenarios where profitability in years $t-2$, $t-1$, and t are [10%, 20%, 30%] and [30%, 20%, 10%] respectively. Despite the identical volatility, these scenarios diverge substantially. The first case, which illustrates increasing profitability over time, is indicative of positive volatility—a higher value suggests a healthier firm. The latter case, however, exposes the firm's risk, with a higher value implying escalating default risk. Given that volatility is but a surrogate for risk and does not directly reflect a firm's intrinsic risk, it is necessary to differentiate between positive and negative volatility to enhance the accuracy of the risk proxy for further analysis. For this purpose, we introduce an interaction term, a *ROA uptrend* dummy, with Risk. The *ROA uptrend* dummy is assigned a value of one when a firm's ROA in years $t-2$, $t-1$, and t demonstrate a non-decreasing trend; otherwise, it is assigned a value of zero. According to our calculations, 19.34% of the sample observations have a *ROA uptrend* dummy of 1, whereas 80.66% of the sample display a *ROA uptrend* dummy of 0.

The results are presented in Table 3.6, but for the sake of conciseness, we omit the results for firm-specific determinants as they echo the results in Table 3.5. As anticipated, the significantly negative impact of Risk on the leverage ratio parallels the results in Table 3.5. The interaction terms between Risk and the *ROA uptrend* dummy consistently exhibit positive significance, implying that healthier firms ($ROA\,uptrend = 1$) maintain significantly higher leverage ratios than riskier firms ($ROA\,uptrend = 0$). Moreover, the joint effects of positive volatility on firm leverage, represented by the summation of Risk and the interaction term, remain positive in all but the last specification.

Difference between SMEs and large firms

Table 3.1 reveals that approximately 95% of the sample observations represent small and medium-sized enterprises (SMEs). However, the risk perception may vary between large firms and SMEs, resulting in divergent leverage ratio responses to risk. Consequently, we introduce an interaction term between Risk and an SME dummy to baseline equation 3.1. It is important to note that we do not include an SME dummy directly, only the interaction term, as our primary regression model already accounts for the size effect.

The findings, presented in Table 3.7, are intriguing and illustrate that SMEs differentiate between long-term and short-term debt. The interaction terms between the SME dummy and Risk for long-term leverage specifications are significantly negative at a 1% confidence level (-0.132 for LL/TA, -0.095 for LD/TC). Contrarily, the interaction term for LD/TA exhibits weak positive significance. However, Welch (2011) advises against relying too heavily on the debt to total assets ratio results as an increase in this ratio does not necessarily indicate an increase in the financial debt ratio; it could be influenced by a decrease in non-financial liabilities.

Significant positive values are observed for short-term leverage and trade credit ratios (0.065 for SL/TA, 0.163 for SD/TA, 0.103 for $Trade/TA$, and 0.216 for SD/TC). Our results indicate that as firms become riskier, the risk reduction effect on long-term financing is more pronounced in SMEs, which face greater constraints on long-term finance than large firms. When SMEs become riskier, they do not reduce their short-term leverage as much as large firms. Instead, they rely more heavily on short-term finance for operations. Compared to long-term finance, short-term finance is more susceptible to roll-over risk, especially in a risky environment. Thus, SMEs' increased reliance on short-term finance raises concerns about the continuity of funding for SMEs during challenging periods.

The analysis, presented in Table 3.7, shows that SMEs exhibit a significantly negative interaction with risk for long-term leverage ratios. Conversely, for short-term leverage and trade credit ratios, SMEs demonstrate a significant positive interaction. This suggests that as SMEs become riskier, they tend to reduce their reliance on long-term financing more than large firms, possibly due to greater constraints in accessing long-term finance. In contrast, their reliance on short-term finance increases, which, while necessary for operations, introduces a greater roll-over risk, particularly in risky environments.

However, if firms strategically choose to remain small to capitalize on benefits specifically available to SMEs, this decision can significantly impact the interpretation of financial behavior, particularly in terms of leverage ratios and risk responses. These firms might not be merely reacting to external constraints or economic conditions but also making a calculated choice to align their financial strategies with the benefits of retaining their SME status. SMEs often have access to favorable financing options, government subsidies, and support programs not available to larger firms. If firms deliberately maintain their SME status, they may be factoring these benefits into their capital structure decisions. This could partly explain the observed tendency for SMEs to rely more on short-term finance, as they may anticipate continued access to SME-specific funding sources that buffer the risks associated with short-term liabilities.

The strategic decision to stay small might influence how SMEs manage risk. These firms might be more willing to accept the roll-over risks associated with short-term financing, knowing that they have ongoing access to SME-targeted financial support that can help mitigate these risks. This could be a reason why, as SMEs become riskier, they do not reduce their short-term leverage as much as large firms, as indicated in the results. Due to the data limitations, we cannot directly test our above arguments. However, this obervation calls for a more nuanced understanding of SME financial behavior and underscores the need to consider the strategic intentions behind maintaining SME status when analyzing financial data and drawing conclusions.

3.5.2 The role of Global Ultimate Owner

Moving to our baseline equation 3.2, we evaluate the impact of Global Ultimate Owner (GUO) type on leverage choice. In this section, we delve into the influence of various GUO types. We use firms without a GUO as the benchmark for the subsequent regressions. As delineated in Figure 1, we categorize our sample into firms with and without a GUO. For firms with a GUO, we further classify them into four distinct GUO types: Industrial, Individual or Family, Financial, and Government. Figure 3.1 displays the distribution of sample observations by GUO type.

Table 3.8 presents our regression findings. We exclude the coefficient of firm-specific determinants, as they closely mirror the baseline model in terms of coefficient signs and magnitudes. Regarding the liability ratios (specifications 1 to 3), firms with a GUO typically have higher current liabilities and fewer non-current liabilities within their capital structure. Firms controlled by a dispersed industry company exhibit the highest short-term liabilities ratio, 5.1 percentage points higher than the benchmark. Conversely, government-controlled firms have the lowest long-term liability ratio, 3.9 percentage points below the benchmark. With respect to the total liability ratio, government-controlled firms have the lowest, while industry company-controlled firms have the highest. On average, industry company-owned firms' total liability ratio is around 5 percentage points higher than that of government-owned companies.

For trade credit (specification 7) and financial debt ratios (specifications 4-6, and 8-10), which bear greater relevance to external financing, we discern a clear pattern reflecting various Global Ultimate Owner (GUO) type impacts. Previous studies typically concentrate on the effect of ownership concentration on leverage choice, thereby neglecting the heterogeneity among different ownership types. We observe that firms with a GUO typically utilize less debt and more trade credit, except in the case of family firms.

In contrast, family firms employ more debt compared to dispersed firms (without a GUO) and firms controlled by other types of GUO. Our results align with studies by Setia-Atmaja et al. (2009), King and Santor (2008), Ellul (2008), and Croci et al. (2011). The firms controlled by the government have the lowest debt ratio, a remarkable 13.6 percentage points below that of family firms, reflecting the risk aversion of the government as the ultimate owner, particularly when it maintains full control over a company.

In terms of the trade credit ratio, we find that family firms, alongside dispersed firms, utilize less trade credit than firms controlled either by an industry company, a financial company, or the government. With regard to trade credit, we propose that non-family ultimate owners may leverage common supplier channels to support their controlled firms. Consequently, firms controlled by non-family owners will exhibit a higher trade credit ratio. Indeed, the highest trade credit ratio is found for firms controlled by an industry GUO, which is 1.1 percentage points above that of family firms. Following this reasoning, we anticipate robust support from the GUO when it operates within the same industry as the subject firm.

We additionally introduce an interaction term between the Global Ultimate Owner (GUO) dummies and Risk to investigate the moderating influence of the ultimate owner on a firm's risk attitude towards leverage choice. The results are detailed in Table 3.9. Primarily, we observe that firm risk continues to exert a negative impact on the leverage ratio. Regarding the financial debt ratio (specifications 4-6 and 8-10), our results indicate that firms with non-family owners tend to display increased risk aversion. The interaction terms for the industrial GUO dummy, financial GUO dummy, and Government GUO dummy are predominantly significantly negative. However, the interaction term for the financial GUO dummy in the SD/TC specification is not significant. Our analysis reveals that family firms tend to rely more heavily on short-term financing in response to risk, compared to other types of firms. The interaction terms between Risk and the family GUO dummy are consistently significantly negative. With respect to the long-term debt ratio, we find no significant insights from the interaction term. Regarding the trade credit ratio, our data suggest that firms with non-family owners are more inclined to resort to trade credit in response to risk. It appears that firms controlled by non-family owners will partially substitute their debt financing for trade credit in risky situations. In contrast, family firms lack the capacity to increase their trade credit and also encounter difficulties in securing long-term financial debt. As a consequence, they tend to utilize more short-term debt compared to other firms to navigate their funding challenges during difficult periods.

3.6 Other robustness tests

3.6.1 Firm capital structure, GUO industry, and GUO capital structure

Further examination is undertaken to determine the influence of a firm and its Global Ultimate Owner (GUO) operating in the same industry on the capital structure. This is achieved by integrating the *Sameindustry* dummy in equation 3.1. In order to contrast the industry sector between the firm and its GUO, our sample is limited to firms with a GUO. Moreover, the nature of the ultimate owner type precludes individuals or families (as no industry sector for this GUO type). This requirement results in the loss of all observations from the two aforementioned subgroups. The resultant sample, used to test the same industry effect, is detailed in Table 3.10. The firm-year observations decrease significantly from 3.75 million to 0.58 million. Despite this reduction, the sample retains a sufficient number of observations for hypothesis testing. Moreover, the remaining 0.58 million sample observations span 12 European countries, indicating no country loss attributable to the sample reduction. Table 3.10 reveals that approximately 23.2% of firms operate in the same industry as their GUO.

Table 3.11 delineates the regression results. It should be noted that the benchmark now refers to the firm controlled by the industry company. The same industry effect is predominantly evident in financial debt ratios (specifications 8 to

10) and trade credit (specification 7), with the total debt ratio and trade credit being 0.7 and 0.5 percentage points higher, respectively, if firms are in the same industry as their ultimate owner. When operating within the same industry, the ultimate owner tends to be more knowledgeable about the business model of its subsidiary firm, which in turn can derive benefit from the owner's expertise. This context could foster greater lender confidence, thereby facilitating SMEs' access to debt financing, at least for short-term finance.

In our second robustness test, we aim to investigate if firms replicate the capital structure of their Global Ultimate Owner (GUO). For this, we collect the various leverage ratios of the firms' GUO and employ them as additional explanatory variables in the corresponding leverage specification regression. For instance, when the dependent variable is the Total Liability Ratio (TL/TA), the equivalent ratio of the GUO is utilized as an additional independent variable. Furthermore, in each specification, we account for profitability, tangibility, and the size of the GUO.

This process further reduces our sample to 0.48 million. The outcomes of this process are presented in Table 3.12. For the sake of brevity, we report only the coefficient of the GUO's leverage ratio. Our primary interest lies in the coefficients of the GUO's leverage ratio. A significantly positive result suggests that firms, to some extent, mimic their GUO's financial policy. From Table 3.12, we observe a significant positive impact of the GUO's leverage ratio after controlling for firm-specific determinants and GUO-specific determinants. Prior literature reviews underscore the peer effect on capital structure, as well as on trade credit (Leary and Roberts (2014)). Compared to peer firms within the same industry, it is more plausible to propose that firms may also emulate their global ultimate owner, given their superior knowledge about their GUO.

3.6.2 Alternative measure of Ownership Concentration

Initially, we used the largest shareholder's direct shareholding to denote a firm's ownership concentration. Furthermore, we incorporated the square term of the direct shareholding to examine the non-linear relationship between ownership concentration and capital structure. However, this measure does not account for the importance of indirect shareholding, wherein a shareholder, through a pyramid structure, can also exert controlling rights of a company.

In this section, we adopt the ownership concentration indicator variable provided by Orbis as an alternative measure for ownership concentration. As explained in Section 3.4.3, Orbis categorizes firms into categories A, B, C, and D based on both direct and total shareholding. Category A represents firms where the largest shareholder controls less than 25% of total shareholding (both direct and indirect). Category B includes firms where the largest shareholder controls between 25% and 50% of total shareholding. Categories C and D comprise firms where the largest shareholder controls more than 50% of total shareholding. The distinction between Categories D and C is that Category D requires the largest shareholder to control more than 50% of direct shareholding. As depicted in Table 3.3, we find that Category C accounts for only 0.55% of the whole sample, so we group Categories C and D together for our regression analysis.

Table 3.13 reports our findings. We observe that the financial debt ratio (specifications 8-10) is lowest for the benchmark (Category A companies) and highest for Category B companies. Regarding the liability ratios (specifications 1-3) and the trade credit ratio (specification 7), we do not observe a decrease in the ratio when moving from Category B to Category C. It is important to note that Category C is bounded by the 50% threshold, and we cannot investigate the impact on capital structure if we further increase this threshold.

3.7 Conclusion

In this paper, we study the capital structure of firms in the Eurozone economy, with a specific emphasis on small and medium-sized enterprises (SMEs). First, we build upon previous research by providing a more exhaustive examination that includes SMEs, large firms, and micro firms from 12 European countries. Our substantial dataset of 625,483 companies allows for broader representation and, thus, enables us to draw more robust generalizations regarding the Eurozone economy than previous studies.

Second, we venture into the relatively unexplored territory of how ownership structure influences a firm's financing decisions. Our findings confirm an inverted U-shaped relationship between ownership concentration and capital structure, previously demonstrated in smaller sample studies of large companies.

Further, we lead the investigation into the effects of various types of ultimate ownership on a firm's capital structure decisions. Rather than merely distinguishing between family and non-family firms, we consider five categories: dispersed firms, family-controlled firms, industrial companies-controlled firms, financial companies-controlled firms, and government-controlled firms. Our analysis reveals that family firms are most likely to use debt, while government firms generally use the least. We further discover that firms tend to replicate the financial policy of their ultimate owners and exhibit a higher likelihood of utilizing more debt when the firm and its Global Ultimate Owner (GUO) operate within the same industry.

Finally, our research highlights the differential impacts of firm-specific determinants on various measures of leverage. Our results reinforce Welch (2011))'s warning against using the leverage defined by financial debt over total assets and endorse Rajan and Zingales (1995) proposition that the ratio of total debt to total capital offers a better representation of past financing decisions.

The findings from this study provide practical implications for Small and Medium Enterprises (SMEs) in managing their capital structures. It is evident that the type of ownership in SMEs - whether family-owned, industry-controlled, financially controlled, or government-operated - significantly influences their leverage decisions. Specifically, family-owned SMEs tend to have higher leverage compared to government-owned ones. This information is crucial for SMEs in making informed decisions about debt management.

Additionally, the research highlights the impact of ownership concentration on capital structure choices, suggesting that SMEs need to carefully consider how equity distribution and decisions on external financing can affect their overall financial strategy. These insights are particularly useful for SMEs when evaluating their options for funding, ensuring that their financial strategies align with their business goals, ownership structure, and risk tolerance.

Overall, this study offers SMEs valuable guidance on how different ownership structures can influence their financial strategies, aiding them in making more strategic and informed financial decisions in a complex economic environment.

3.8 Figures and Tables

Figure 3.1: Sample distribution of GUO

This figure illustrates the sample distribution by different GUO (global ultimate owner) types. We categorize firms into 5 different groups. “noguo” stands for firms that don’t have a GUO; “Industry type” stands for firms owned by another industrial company; “Individual or families” stands for firms owned by an individual or a family; “Financial type” stands for firms owned by a financial company; “Government type” stands for firms owned by the government. The sample period is from 2007 to 2014.

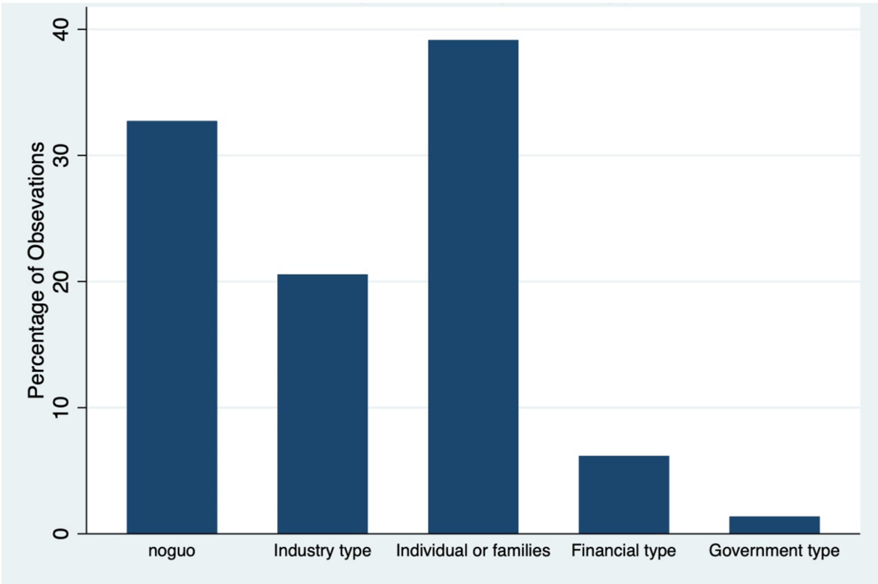


Table 3.1: Summary Statistics

This table shows summary statistics for the independent variables and dependent variables used in our regression analysis. The first ten are different leverage measures: TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. $Size$ is the log value of the total assets in thousand; AGE is the log value of the number of days since incorporation divided by 365; $Tangibility$ is the ratio of tangible assets to total assets; $Profitability$ is the ratio of profit before tax to total assets; $Risk$ the three years ($t-2$,$t-1$,t)rolling volatility of $Profitability$; $SaleGrowth$ is the annual percentage change in sales revenue; $OWN\,Concentration$ is the percentage of largest shareholder direct shareholding; A firm-year observation is classified as an SME if a firm's total asset is less than €43 million. The sample period covers from 2007 to 2014.

Variable	N.	Mean	SD	Min	P25	Median	P75	Max
TL/TA	3,672,788	0.673	0.264	0.016	0.498	0.700	0.862	2.440
LL/TA	3,672,788	0.162	0.195	0.000	0.015	0.090	0.238	1.228
SL/TA	3,672,788	0.509	0.265	0.000	0.308	0.504	0.702	1.685
Trade/TA	3,650,918	0.206	0.189	0.000	0.052	0.159	0.308	1.007
TD/TA	3,426,323	0.183	0.207	0.000	0.001	0.109	0.303	1.180
LD/TA	3,440,395	0.106	0.167	0.000	0.000	0.024	0.148	1.448
SD/TA	3,656,778	0.076	0.121	0.000	0.000	0.012	0.105	0.745
TD/TC	3,424,434	0.330	0.347	-1.014	0.001	0.238	0.585	2.823
LD/TC	3,424,434	0.177	0.257	-0.886	0.000	0.047	0.275	2.823
SD/TC	3,424,434	0.152	0.233	-0.252	0.000	0.028	0.222	1.222
Size	3,672,788	7.922	1.439	4.248	6.916	7.734	8.710	16.906
Age	3,672,788	2.753	0.734	0.379	2.273	2.841	3.262	4.995
Tangibility	3,672,788	0.209	0.230	0.000	0.033	0.117	0.313	0.974
Profitability	3,672,788	0.052	0.124	-0.646	0.003	0.033	0.097	0.691
Risk	3,672,788	0.054	0.070	0.000	0.014	0.032	0.066	0.659
Sales Growth	3,672,788	0.138	0.896	-0.996	-0.085	0.024	0.152	13.213
OWN Concentration	3,672,788	0.714	0.275	0.001	0.500	0.743	1.000	1.000
SME	3,672,788	0.949	0.220	0.000	1.000	1.000	1.000	1.000

Table 3.2: Leverage by country

This table shows the mean value of TL/TA, $Trade/TA$, TD/TA, TD/TC, and SME by country. The second row in each country code shows the number of observations in that country. TL/TA is the ratio of total liabilities to total assets; Trade/TA is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; TD/TC is the ratio of total financial debt to total capital. Total capital is defined as the sum of total shareholder funds plus total financial debt. A firm-year observation is classified as an SME if a firm's total asset is less than €43 million.

Country	TL/TA	Trade/TA	TD/TA	TD/TC	SME/TA
Belgium	0.635	0.220	0.165	0.276	0.853
	71,412	71,412	71,408	71,398	71,412
Switzerland	0.562	0.080	0.264	0.350	0.356
	1,908	1,908	1,818	1,818	1,908
Germany	0.657	0.115	0.197	0.328	0.782
	164,622	153,197	153,216	151,817	164,622
Spain	0.604	0.163	0.263	0.411	0.954
	634,055	625,975	518,188	518,161	634,055
Finland	0.630	0.116	0.201	0.328	0.944
	57,546	57,525	47,208	47,198	57,546
France	0.649	0.238	0.122	0.241	0.961
	878,522	878,522	878,398	878,251	878,522
Greece	0.632	0.235	0.262	0.388	0.936
	67,713	67,713	67,713	67,711	67,713
Italy	0.738	0.232	0.183	0.367	0.964
	1,206,337	1,206,337	1,206,337	1,206,097	1,206,337
Netherlands	0.640	0.132	0.215	0.372	0.601
	7,041	5,412	2,226	2,226	7,041
Norway	0.700	0.158	0.137	0.241	0.964
	212,276	212,275	212,274	212,257	212,276
Portugal	0.673	0.219	0.302	0.474	0.972
	230,061	229,367	157,458	157,425	230,061
Sweden	0.616	0.132	0.136	0.231	0.941
	141,295	141,275	110,079	110,075	141,295

Table 3.3: Distribution of Ownership Concentration

This table shows the sample observations by independent indicator. A stands for a firm with recorded largest shareholder with less than 25% direct or total shareholdings; B stands for a firm with recorded largest shareholder with direct or total shareholdings between 25% and 50%; C stands for a firm with recorded largest shareholder with greater than 50% total or direct shareholdings. D stands for a firm with recorded largest shareholder with greater than 50% direct shareholdings. The sample period ranges from 2007 to 2014.

Ownership Concentration	N.	Percent
A (<25%)	211,939	5.77
B (25%-50%)	990,122	26.96
C (>50%)	20,325	0.55
D (>50%)	2,450,402	66.72

Table 3.4: Summary statistics by independence indicator

This table shows the mean value of the independent variables and dependent variables used in regressions by the independence indicator. A stands for a firm with recorded largest shareholder with less than 25% direct or total shareholdings; B stands for a firm with recorded largest shareholder with direct or total shareholdings between 25% and 50%; C stands for a firm with recorded largest shareholder with greater than 50% total or direct shareholdings. Here we group independence indicators C and D to C in table **??**. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. *Size* is the log value of the total assets in thousand; AGE is the log value of the number of days since incorporation divided by 365; *Tangibility* is the ratio of tangible assets to total assets; $Profitability$ is the ratio of profit before tax to total assets; *Risk* the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$; *SaleGrowth* is the annual percentage change in sales revenue; $OWN\,Concentration$ is the percentage of largest shareholder direct shareholding; A firm-year observation is classified as an SME if a firm's total asset is less than €43 million. The sample period covers from 2007 to 2014.

Variable	Ownership Concentration		
	A(<25%)	B(25%-50%)	C(>50%)
TL/TA	0.635	0.672	0.677
LL/TA	0.174	0.168	0.159
SL/TA	0.459	0.502	0.516
Trade/TA	0.189	0.212	0.204
TD/TA	0.198	0.199	0.175
LD/TA	0.115	0.112	0.103
SD/TA	0.081	0.086	0.071
TD/TC	0.339	0.357	0.319
LD/TC	0.184	0.186	0.173
SD/TC	0.154	0.171	0.145
Size	8.114	7.650	8.014
Age	2.874	2.754	2.743
Tangibility	0.240	0.223	0.200
Profitability	0.046	0.047	0.058
Sales Growth	0.132	0.134	0.140
Risk	0.040	0.049	0.054
OWN Concentration	0.249	0.440	0.863
SME	0.947	0.979	0.937

Table 3.5: Leverage, Risk and Ownership concentration

This table reports the estimated coefficients for the OLS regressions of equation **??** and their t statistics clustered at the firm level (in bracket). The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. $Size$ is the log value of the total assets in thousand; AGE is the log value of the number of days since incorporation divided by 365; $Tangibility$ is the ratio of tangible assets to total assets; $Profitability$ is the ratio of profit before tax to total assets; $Risk$ the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$; $SaleGrowth$ is the annual percentage change in sales revenue; $OWN\,Concentration$ is the percentage of largest shareholder direct shareholding; A firm-year observation is classified as an SME if a firm's total assets are worth no more than €43 million. In each specification, we control for country, industry, and year fixed effects. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

VARIABLES	(1) TL/TA	(2) LL/TA	(3) SL/TA	(4) TD/TA	(5) LD/TA	(6) SD/TA	(7) Trade/TA	(8) TD/TC	(9) LD/TC	(10) SD/TC
Tangibility	-0.059***	0.266***	-0.329***	0.215***	0.230***	-0.013***	-0.187***	0.207***	0.306***	-0.099***
	[-39.396]	[221.180]	[-253.635]	[168.956]	[216.896]	[-22.793]	[-235.740]	[108.356]	[204.988]	[-92.667]
Profitability	-0.716***	-0.253***	-0.445***	-0.346***	-0.178***	-0.156***	-0.172***	-0.687***	-0.327***	-0.349***
	[-291.402]	[-183.311]	[-197.623]	[-232.765]	[-155.564]	[-201.459]	[-135.768]	[-238.405]	[-173.361]	[-215.360]
Age	-0.070***	-0.020***	-0.049***	-0.025***	-0.022***	-0.002***	-0.025***	-0.057***	-0.041***	-0.015***
	[-174.497]	[-70.758]	[-126.676]	[-78.581]	[-90.945]	[-13.533]	[-91.874]	[-108.036]	[-111.399]	[-43.746]
Size	-0.012***	0.012***	-0.024***	0.013***	0.007***	0.005***	-0.014***	0.007***	0.004***	0.003***
	[-49.720]	[70.074]	[-104.966]	[67.296]	[44.063]	[48.604]	[-91.814]	[23.723]	[17.469]	[16.369]
Sales Growth	0.011***	0.006***	0.006***	0.004***	0.006***	-0.001***	0.003***	0.009***	0.010***	-0.001***
	[69.948]	[36.030]	[31.332]	[27.641]	[43.785]	[-16.926]	[22.443]	[35.340]	[49.065]	[-8.075]
Risk	0.182***	-0.014***	0.169***	-0.122***	-0.062***	-0.061***	-0.059***	-0.322***	-0.130***	-0.198***
	[37.806]	[-4.885]	[40.011]	[-40.324]	[-25.667]	[-40.783]	[-23.167]	[-57.819]	[-33.255]	[-67.060]
OWN Concentration	0.025***	0.021***	0.009	0.093***	0.044***	0.049***	0.012**	0.157***	0.073***	0.088***
	[3.382]	[4.221]	[1.254]	[16.434]	[10.477]	[14.920]	[2.454]	[17.245]	[11.571]	[14.260]
OWN Concentration^2	0.025***	-0.020***	0.041***	-0.085***	-0.042***	-0.043***	0.001	-0.124***	-0.061***	-0.068***
	[4.600]	[-5.678]	[8.184]	[-20.358]	[-13.432]	[-17.933]	[0.139]	[-18.585]	[-13.104]	[-14.974]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.215	0.221	0.234	0.195	0.240	0.099	0.191	0.144	0.196	0.122
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.6: "Good" volatility VS "Bad" volatility

This table reports the estimated coefficients of interaction between $Risk$ and the profitability $ROAUptrend$ dummy in equation 3.1, and their t statistics clustered at the firm level (in bracket). $Risk$ the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$ measured by ROA. The $ROAUptrend$ dummy takes the value of one when a firm's ROA in years $t-2$, $t-1$, and t are always non-decreasing. The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. In each specification, we control for country, industry, and year fixed effects. We also control for firm-specific determinants used in table 3.5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
Risk	0.029***	-0.067***	0.072***	-0.180***	-0.096***	-0.084***	-0.096***	-0.448***	-0.195***	-0.257***
	[5.734]	[-22.129]	[16.354]	[-56.394]	[-37.569]	[-52.766]	[-35.526]	[-76.118]	[-47.254]	[-80.798]
Risk x ROA Uptrend	0.634***	0.218***	0.398***	0.240***	0.139***	0.096***	0.152***	0.522***	0.267***	0.241***
	[104.777]	[59.024]	[75.330]	[64.327]	[45.947]	[52.909]	[48.561]	[68.734]	[51.098]	[61.235]
OWN Concentration	0.027***	0.021***	0.010	0.094***	0.045***	0.050***	0.013**	0.159***	0.074***	0.089***
	[3.687]	[4.375]	[1.455]	[16.602]	[10.601]	[15.026]	[2.561]	[17.481]	[11.732]	[14.413]
OWN Concentration^2	0.023***	-0.021***	0.040***	-0.085***	-0.042***	-0.044***	0.000	-0.126***	-0.062***	-0.068***
	[4.306]	[-5.844]	[7.989]	[-20.546]	[-13.569]	[-18.048]	[0.027]	[-18.843]	[-13.281]	[-15.141]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.222	0.222	0.237	0.196	0.241	0.100	0.192	0.147	0.197	0.123
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.7: SME vs Large firms

This table reports the estimated coefficients of interaction between *Risk* and the *SME* dummy in equation 3.1, and their t statistics clustered at the firm level (in bracket). *Risk* the three years ($t-2$, $t-1$, t) rolling volatility of *Profitability* measured by ROA. The *SME* dummy takes the value of one if a firm's total asset is less than €43 million. The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. *Totalcapital* is defined as the sum of total shareholder funds plus total financial debt. In each specification, we control for country, industry, and year fixed effects. We also control for firm-specific determinants used in table 3.5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
Risk	0.254***	0.112***	0.107***	-0.291***	-0.087***	-0.217***	-0.157***	-0.417***	-0.040**	-0.404***
	[12.652]	[8.053]	[5.852]	[-19.140]	[-7.091]	[-31.301]	[-18.218]	[-17.293]	[-2.213]	[-33.279]
Risk x SME	-0.075***	-0.132***	0.065***	0.177***	0.026**	0.163***	0.103***	0.100***	-0.095***	0.216***
	[-3.685]	[-9.387]	[3.486]	[11.577]	[2.088]	[23.310]	[11.647]	[4.075]	[-5.137]	[17.500]
OWN Concentration	0.025***	0.020***	0.009	0.094***	0.045***	0.050***	0.012**	0.157***	0.073***	0.088***
	[3.356]	[4.151]	[1.279]	[16.518]	[10.494]	[15.052]	[2.507]	[17.274]	[11.531]	[14.360]
OWN Concentration^2	0.025***	-0.020***	0.041***	-0.085***	-0.042***	-0.044***	0.000	-0.125***	-0.061***	-0.068***
	[4.627]	[-5.608]	[8.160]	[-20.443]	[-13.449]	[-18.067]	[0.086]	[-18.614]	[-13.065]	[-15.075]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.215	0.221	0.234	0.195	0.240	0.100	0.191	0.144	0.196	0.122
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.8: Global Ultimate Owner and Leverage in the owned firm - A

This table reports the estimated coefficients for the OLS regressions of equation 3.2 and their t statistics clustered at the firm level (in bracket). *Industrial* dummy equals one if the firm is controlled by another industrial company; *Financial* dummy equals one if the firm is controlled either by a Bank, Financial company, Foundation/Research Institute, Insurance company, Private Equity firm, Venture capital, Mutual & Pension Fund/Nominee/Trust/Trustee; $IndividualorFamilies$ dummy equals one if the firm is controlled by an individual or a family; *Government* dummy equals one if the firm is controlled by Public authority, State, or Government. The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. In each specification, we control for country, industry, and year fixed effects. We also control for firm-specific determinants used in table 3.5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
Industiral	0.041***	-0.011***	0.051***	-0.033***	-0.019***	-0.015***	0.011***	-0.041***	-0.025***	-0.018***
	[43.851]	[-18.444]	[57.871]	[-47.346]	[-36.733]	[-37.429]	[18.740]	[-35.839]	[-31.162]	[-23.537]
Individual or Families	0.012***	-0.001**	0.012***	0.002***	0.001**	0.002***	0.000	0.010***	0.004***	0.006***
	[17.429]	[-2.252]	[19.685]	[3.829]	[1.983]	[5.036]	[0.938]	[11.390]	[5.984]	[10.260]
Financial	0.029***	-0.005***	0.033***	-0.018***	-0.012***	-0.007***	0.006***	-0.022***	-0.016***	-0.007***
	[20.966]	[-5.802]	[25.017]	[-17.024]	[-14.860]	[-12.606]	[6.523]	[-12.891]	[-13.566]	[-6.665]
Government	-0.006**	-0.039***	0.033***	-0.089***	-0.061***	-0.032***	0.010***	-0.126***	-0.083***	-0.044***
	[-2.005]	[-16.214]	[11.896]	[-38.483]	[-30.405]	[-33.963]	[6.454]	[-35.147]	[-29.476]	[-22.644]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.214	0.221	0.234	0.199	0.243	0.101	0.191	0.147	0.198	0.123
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.9: Global Ultimate Owner, Leverage in the owned firm and ROA volatility - B

This table reports the estimated coefficients of interaction between *Risk* and the GUO dummies in equation 3.2, and their t statistics clustered at the firm level (in bracket). *Risk* the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$ measured by ROA. *Industrial* dummy equals one if the firm is controlled by another industrial company; *Financial* dummy equals one if the firm is controlled either by a Bank, Financial company, Foundation/Research Institute, Insurance company, Private Equity firm, Venture capital, Mutual & Pension Fund/Nominee/Trust/Trustee; $IndividualorFamilies$ dummy equals one if the firm is controlled by an individual or a family; *Government* dummy equals one if the firm is controlled by Public authority, State, or Government. The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. In each specification, we control for country, industry, and year fixed effects. We also control for firm-specific determinants used in table 3.5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

VARIABLES	(1) TL/TA	(2) LL/TA	(3) SL/TA	(4) TD/TA	(5) LD/TA	(6) SD/TA	(7) Trade/TA	(8) TD/TC	(9) LD/TC	(10) SD/TC
Risk	-0.045***	-0.006	-0.058***	-0.070***	-0.018***	-0.049***	-0.113***	-0.277***	-0.079***	-0.196***
	[-5.296]	[-1.255]	[-7.845]	[-13.851]	[-4.621]	[-18.779]	[-26.032]	[-29.202]	[-11.946]	[-38.064]
Risk x Industrial	0.439***	-0.016**	0.440***	-0.157***	-0.112***	-0.052***	0.110***	-0.185***	-0.141***	-0.063***
	[39.887]	[-2.420]	[45.945]	[-23.430]	[-21.126]	[-15.800]	[19.676]	[-14.852]	[-16.318]	[-9.606]
Risk x Individual or Families	0.203***	-0.007	0.200***	0.009	-0.004	0.012***	0.042***	0.065***	0.013	0.050***
	[20.408]	[-1.331]	[22.955]	[1.486]	[-0.863]	[3.957]	[8.046]	[5.809]	[1.621]	[8.149]
Risk x Financial	0.373***	-0.004	0.363***	-0.086***	-0.080***	-0.015***	0.073***	-0.082***	-0.101***	-0.003
	[23.233]	[-0.473]	[25.740]	[-8.579]	[-9.957]	[-3.054]	[9.268]	[-4.405]	[-7.793]	[-0.309]
Risk x Government	0.228***	-0.176***	0.400***	-0.518***	-0.399***	-0.135***	0.100***	-0.800***	-0.578***	-0.238***
	[5.982]	[-7.486]	[11.932]	[-19.646]	[-18.761]	[-12.061]	[5.986]	[-19.599]	[-20.784]	[-11.917]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.214	0.221	0.233	0.195	0.241	0.099	0.191	0.145	0.197	0.122
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.10: Tabulate by GUO type and Same industry

This table reports the sample distribution of firms when they are in the same industry as their global ultimate owner

GUO type	Not Same Industry	Same industry	Total
Industry type	318,676	128,803	447,479
Financial type	129,098	6,194	135,292
Government type	4,319	5	4,324
Total	452,093	135,002	587,095

Table 3.11: Same industry effect

This table reports the estimated coefficients for the OLS regressions of equation 3.1 with an additional $SameIndustry$ dummy and their t statistics clustered at the firm level (in bracket). The $SameIndustry$ dummy equals one if the industry sector of the firm is the same as the industry sector of its global ultimate owner. The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans(include financial debt less than one year)to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. $Risk$ the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$; $SaleGrowth$ is the annual percentage change in sales revenue; $OWN\,Concentration$ is the percentage of largest shareholder direct shareholding; In each specification, we control for country, industry, and year fixed effects. We also control for the firm-specific determinants used in table 3.5. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
OWN Concentration	-0.063	0.003	-0.058	0.195***	0.047*	0.148***	0.087***	0.301***	0.083**	0.231***
	[-1.400]	[0.105]	[-1.419]	[5.723]	[1.835]	[7.670]	[2.767]	[5.944]	[2.247]	[7.015]
OWN Concentration^2	0.083***	-0.009	0.086***	-0.153***	-0.046***	-0.108***	-0.062***	-0.222***	-0.068***	-0.164***
	[2.866]	[-0.476]	[3.224]	[-6.877]	[-2.700]	[-8.557]	[-3.040]	[-6.698]	[-2.824]	[-7.587]
Risk	0.352***	0.042***	0.284***	-0.079***	-0.046***	-0.033***	-0.013**	-0.194***	-0.079***	-0.131***
	[34.043]	[6.257]	[30.739]	[-11.614]	[-8.137]	[-10.677]	[-2.370]	[-15.869]	[-8.848]	[-21.388]
Same Industry	0.009***	-0.003**	0.012***	-0.000	-0.000	0.000	0.005***	0.007***	0.003*	0.004***
	[4.996]	[-2.043]	[6.796]	[-0.232]	[-0.372]	[0.405]	[4.598]	[2.963]	[1.715]	[2.763]
Observations	587,095	587,095	587,095	540,035	542,137	584,529	583,469	539,439	539,439	539,439
R-squared	0.195	0.238	0.218	0.217	0.233	0.086	0.215	0.148	0.188	0.090
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.12: Impact of Global Ultimate Owner Leverage

This table reports the estimated coefficients for the OLS regressions of equation 3.1 with an additional GUO leverage variable and their t statistics clustered at the firm level (in bracket). The dependent variables are various leverage measures. $Guo\,TL/TA$ is the ratio of total liabilities to total assets of its GUO; $Guo\,LL/TA$ is the ratio of non-current liabilities to total assets of its GUO; $Guo\,SL/TA$ is the ratio of current liabilities to total assets of its GUO; $Guo\,Trade/TA$ is the ratio of trade payables to total assets of its GUO; $Guo\,TD/TA$ is the ratio of total financial debt to total assets of its GUO; $Guo\,LD/TA$ is the ratio of long-term financial debt to total assets of its GUO; $Guo\,SD/TA$ is the ratio of short-term loans (include financial debt less than one year) to total assets of its GUO; $Guo\,TD/TC$ is the ratio of total financial debt to total capital of its GUO; $Guo\,LD/TC$ is the ratio of long-term financial debt to total capital of its GUO; $Guo\,SD/TC$ is the ratio of short-term loans to total capital of its GUO. In each specification, we control for country, industry, and year fixed effects. We also control for the firm-specific determinants used in table 3.5 and the size, tangibility, and profitability of its GUO. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
Guo TL/TA	0.127***									
	[44.303]									
Guo LL/TA		0.089***								
		[33.030]								
Guo SL/TA			0.121***							
			[37.501]							
Guo TD/TA				0.102***						
				[32.563]						
Guo LD/TA					0.079***					
					[26.133]					
Guo SD/TA						0.120***				
						[32.341]				
Guo Trade/TA							0.159***			
							[25.519]			
Guo TD/TC								0.145***		
								[37.864]		
Guo LD/TC									0.101***	
									[29.491]	
Guo SD/TC										0.172***
										[34.992]
Observations	484,463	480,021	484,306	414,074	419,758	473,957	473,980	413,607	413,607	413,607
R-squared	0.214	0.243	0.222	0.245	0.253	0.112	0.217	0.179	0.210	0.115
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3.13: Leverage, Risk and Ownership concentration

This table reports the estimated coefficients for the OLS regressions of equation 3.1 and their t statistics clustered at the firm level (in bracket). The dependent variables are various leverage measures. TL/TA is the ratio of total liabilities to total assets; LL/TA is the ratio of non-current liabilities to total assets; SL/TA is the ratio of current liabilities to total assets; $Trade/TA$ is the ratio of trade payables to total assets; TD/TA is the ratio of total financial debt to total assets; LD/TA is the ratio of long-term financial debt to total assets; SD/TA is the ratio of short-term loans (include financial debt less than one year) to total assets; TD/TC is the ratio of total financial debt to total capital; LD/TC is the ratio of long-term financial debt to total capital; SD/TC is the ratio of short-term loans to total capital. $Totalcapital$ is defined as the sum of total shareholder funds plus total financial debt. $CategoryB$ is a dummy equal to one if the firm's largest shareholder has a total shareholding between 25% and 50%; $CategoryC$ is a dummy equal to one if the firm's largest shareholder has a total shareholding of more than 50%; $Size$ is the log value of the total assets in thousand; AGE is the log value of the number of days since incorporation divided by 365; $Tangibility$ is the ratio of tangible assets to total assets; $Profitability$ is the ratio of profit before tax to total assets; *Risk* the three years ($t-2$, $t-1$, t) rolling volatility of $Profitability$; *SaleGrowth* is the annual percentage change in sales revenue; A firm-year observation is classified as an SME if a firm's total assets are worth no more than €43 million. In each specification, we control for country, industry, and year fixed effects. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period covers from 2007 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	TL/TA	LL/TA	SL/TA	TD/TA	LD/TA	SD/TA	Trade/TA	TD/TC	LD/TC	SD/TC
Tangibility	-0.060***	0.266***	-0.330***	0.215***	0.230***	-0.013***	-0.187***	0.207***	0.306***	-0.099***
	[-40.133]	[221.235]	[-254.181]	[169.104]	[216.972]	[-22.481]	[-236.046]	[108.385]	[204.991]	[-92.586]
Profitability	-0.717***	-0.253***	-0.446***	-0.346***	-0.178***	-0.156***	-0.172***	-0.687***	-0.326***	-0.349***
	[-290.793]	[-183.285]	[-197.229]	[-232.405]	[-155.357]	[-201.228]	[-135.759]	[-238.190]	[-173.197]	[-215.187]
Age	-0.071***	-0.020***	-0.050***	-0.024***	-0.022***	-0.002***	-0.025***	-0.057***	-0.041***	-0.015***
	[-177.597]	[-70.630]	[-129.974]	[-77.272]	[-90.268]	[-12.265]	[-93.142]	[-107.720]	[-111.234]	[-43.409]
Size	-0.011***	0.012***	-0.023***	0.012***	0.006***	0.005***	-0.014***	0.007***	0.004***	0.003***
	[-45.489]	[70.244]	[-100.410]	[65.190]	[42.995]	[46.494]	[-90.622]	[22.658]	[16.866]	[15.212]
Sales Growth	0.011***	0.006***	0.006***	0.004***	0.006***	-0.001***	0.003***	0.009***	0.010***	-0.001***
	[70.074]	[36.049]	[31.394]	[27.648]	[43.793]	[-16.913]	[22.467]	[35.380]	[49.097]	[-8.047]
Risk	0.191***	-0.015***	0.178***	-0.126***	-0.064***	-0.063***	-0.057***	-0.326***	-0.132***	-0.200***
	[39.617]	[-5.124]	[42.162]	[-41.682]	[-26.495]	[-42.199]	[-22.373]	[-58.392]	[-33.675]	[-67.694]
Category B	0.021***	0.004***	0.017***	0.010***	0.005***	0.005***	0.003***	0.021***	0.010***	0.010***
	[15.604]	[4.608]	[13.738]	[9.240]	[6.350]	[7.911]	[3.728]	[12.207]	[8.784]	[9.016]
Category C	0.037***	-0.001	0.037***	-0.001	-0.002**	0.001	0.006***	0.011***	0.003**	0.007***
	[28.303]	[-0.993]	[31.297]	[-0.979]	[-2.342]	[1.072]	[7.339]	[6.556]	[2.288]	[6.829]
Observations	3,672,788	3,672,788	3,672,788	3,426,323	3,440,395	3,656,778	3,650,918	3,424,434	3,424,434	3,424,434
R-squared	0.213	0.221	0.232	0.194	0.240	0.099	0.191	0.144	0.196	0.122
Country effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Chapter 4

The Impact of Global Warming on Small and Micro European Firms

4.1 Introduction

The physical risk events induced by global warming are now more frequent and intense than ever. The dire consequences of climate change are being felt by people and corporations around the world. Wildfires, floods, droughts, and crop failures have all become more frequent and severe. Recent events have provided stark examples of what is expected to become an established trend.* Our planet's

*In 2021, two severe floods hit Europe and China. The European floods affected Germany, Belgium, Romania, and Italy and caused more than 200 deaths and billions of dollars of damage.

temperature has so far increased by 0.85°C compared to preindustrial levels (Carleton and Hsiang (2016)). Warming is becoming more rapid, and the global temperature is likely to increase by 1.5°C over the coming decades (IPCC (2022)). Moreover, without actively controlling carbon emissions, it may not be possible to limit global warming to 1.5-2°C, a limit jointly established by 194 countries in the 2015 Paris Agreement.

In this paper, we look at the physical risk of climate change, with particular focus on the impact on the small-business sector of extremely high temperature. The economic importance of weather differences across regions and countries has long been documented in the literature. Dell et al. (2014) show that previous studies have identified a negative relationship between temperature and per capita income, aggregate output, agriculture output, and labour productivity (see also, Gates (1967), Huntington (1924), Montesquieu (1989)). More recent studies have taken advantage of the longitudinal data that allows researchers to identify the causal effects of climate change. Hsiang (2010) considers 28 Caribbean-basin countries and finds that national output decreases by 2.5% when temperature increases by 1°C. Dell et al. (2012) find a negative impact of raising temperature on income in poor countries, but little evidence of it in rich countries. Panel estimates for developing countries typically find a negative

The Chinese flood was triggered by a record-breaking amount of rainfall in the Henan Province. According to official reports, this flash flood led to $18 billion of damage and 398 deaths (including missing people). In July 2022, UK citizens experienced temperatures of above 40°C for the first time since record began. In the same month, a heatwave in Portugal led to a historical high temperature of 47°C, causing 1,063 deaths between 7 and 18 July.

relationship between bad weather and agricultural output (Lobell et al. (2011), Guiteras (2009), Welch et al. (2010), Feng et al. (2010)). In terms of the effect of temperature on productivity, results from controlled lab experiments show that there is a 2% productivity loss per 1°C increase in temperature, but only when the temperature is above 25°C (Seppanen et al. (2003)). Graff Zivin and Neidell (2014) also find that hot days, especially when temperatures are extreme, reduce the activities of outdoor industries.

Recent papers have investigated whether the macro effects reported above also transfer to corporate performance. Despite an abundance of literature exploring whether climate risk is priced into equity prices (Balvers et al. (2017), Bolton and Kacperczyk (2021), Engle et al. (2020), Hong et al. (2019)), little is known about how climate risk affects firm performance. The existing evidence is limited, inconclusive, and focused largely on US public-listed companies. Large corporations have business operations distributed over wide geographical areas and even across international borders. Thus, these companies might be more resilient to extreme local weather events. By contrast, the effect of climate change on small and micro enterprises – which account for the vast majority of firms worldwide and are more likely to be disrupted by increases in local temperatures – have not been the object of any systematic investigation. This study seeks to fill this gap. We combine granular weather data with financial reports for small and micro firms with the aim of testing and assessing the effects of climate change on the profitability of these firms.

We contribute to the literature in the following ways. First, to the best of our knowledge, our paper is the first study to systematically examine the effect of increasing temperatures on the performance of small and micro European enterprises. We use a fine grid of weather data with cells measuring 0.1° latitude by 0.1° longitude. We accurately match firms and weather data by geocoding the postcodes of each firm's registered address and minimising the distances between the locations of the firms' headquarters and the centres of the square cells on the temperature grid. Given the local nature of small and micro firms' operations and the high-resolution E-OBS weather data we employ, our matched firm-specific weather variables are able to reflect precise weather exposure at the firm level. Following the suggestions in the climate economic literature (e.g., Dell et al. (2012), Dell et al. (2014)), we run a panel regression model with a battery of fixed effects. To avoid "over-controlling", as suggested by Addoum et al. (2020), we do not include other firm-specific covariates in the regression. Our main finding is that, with a 1°C increase in mean temperature, a firm's operating income decreases by 6.8%. This result is statistically significant at the 1% level.

These results differ from those of Addoum et al. (2020), who study large US corporations. They first match daily temperature data with sales at the establishment level and then investigate how temperature variability affects the firms' sales and profitability. Both the establishment- and firm-level results show that sales, profitability, and productivity are generally unaffected by temperature shocks. By contrast, a later study by the same authors (Addoum et al. (2023)) concludes that, in 40% of the US industry sectors they analyse, firms' quarterly earnings exhibit sensitivity to temperature. Investigating worldwide data for medium and large companies, Pankratz et al. (2023) find that extremely high temperatures result in a drop in firms' revenues and operating income. Similarly, Custodio et al. (2022) observe that a 1°C increase in average daily temperature decreases sales to the same customer by 2%. Our focus on small and micro firms complements and extends the above studies. Small companies are more susceptible to adverse weather conditions, as they are often operating with fewer resources, limited access to funding, and geographically concentrated assets. Large firms, in contrast, are more likely to have large inventories, multiple funding sources, and dispersed activities, which may help them to cope with local shocks in temperature and make it more difficult for researchers to establish any causal effect between changes in weather or climate and a firm's productivity.

Our second contribution to the literature is an exploration of the channels through which temperature shocks can affect firm performance. First, we explore whether our results are driven by firm size. We find that both small and micro firms are significantly and negatively affected by temperature shocks. However, the effect on profitability of rising mean temperature is 35.1% larger for micro firms. Hence, we conclude that vulnerability to climate change is inversely related to firm size. We also explore how financial constraints affect a firm's ability to withstand climate risk. Limited access to external finance may impair a firm's ability to adapt to climate risk, which might in turn affect its performance. Custodio et al. (2022) find a 1.5–2 times larger impact of temperature on sales for financially constrained firms, compared with their baseline model. We apply the financial-constraint measure proposed by Schauer et al. (2019) and find that financially constrained firms are more negatively affected across all our measures of temperature shock. We also test other measures of financial constraints and the results remain the same. Finally, we consider whether the financial-constraint effect is driven purely by firm size. To address this, we run separate analyses of the micro- and small-firm groups. For each sub-sample, we observe a stronger negative effect of temperature shocks for financially constrained firms.

We also investigate whether temperature changes had heterogeneous impacts on different industries. We find that the performance of energy and utility firms is positively affected by higher temperatures. This may be because demand for these sectors actually increases as a result of climate change.

Our third contribution is an analysis of whether the ownership structure of a firm can influence its response to climate risk and, hence, its performance. For instance, institutional investors can influence how business owners run their companies and play an important role in business decision-making (Gillan and Starks (2003)). Using ownership data from Orbis, we divide the firms into four categories according to whether the largest owner is a non-financial company, a financial company, a family, or the government. We find that family-owned businesses suffer less from rising temperatures, while government-controlled firms do not seem to be sensitive to temperature shocks. The reduction of agency costs within the firm, when owners hold management positions, can also help to reduce the negative effects of high temperatures.

The rest of the paper is organised as follows. Chapter 2 presents the data. In Chapter 3, we describe the methodology. The empirical results and the implications of our findings are discussed in Chapter 4. Chapter 5 discusses a range of robustness checks and Chapter 6 presents the conclusion.

4.2 Data and Summary Stats

4.2.1 Sample and Variables

We collect financial and ownership data from Orbis Bureau van Dijk for small and micro firms, from 2005 to 2014. Following the European Commission definition, we define "small firms" as those with a total asset value of between 2 and 10 million Euros and "micro firms" as companies with an asset value of less than 2 million Euros.[†] In our final data, 42.19% of the observations are small firms and

[†]The European Commission also uses staff headcount in their classification criteria (see https://single-market-economy.ec.europa.eu/smes). We do not consider staff headcount because the coverage of this type of information in the Orbis database is not comprehensive.

57.81% are micro firms. We remove firms that operate in the public sector or the financial industry, in line with the traditional corporate finance literature.[‡] We conduct a set of extensive validation checks of the data and exclude unreliable observations. For example, we filter out records with missing variables and firms for which the location of the headquarter is not given. We also exclude countries with fewer than 900 firm-year observations. Following these checks, we are left with approximately 7 million firm-year observations.

The climate data is collected from E-OBS, which is a daily gridded land-only observational dataset for Europe. Dell et al. (2014) provide a detailed explanation of the types of weather data that should be used for economic analysis. There are four general types: stationary data, gridded data, satellite data, and reanalysis data. Gridded data is popular because it uses statistical projections over a grid to increase the data coverage. For example, US weather studies often rely on temperature and precipitation data from the PRISM group, which interpolates weather data at each 4km by 4km cell of the weather grid. Although the E-OBS is generally used to monitor the European climate, it has not been widely used in the finance literature. We collect data on daily mean temperature, daily minimum temperature, daily maximum temperature, and daily precipitation from 1973–2014. The weather data from 1973 to 2003 are used to calculate the historical quantile value of maximum and minimum temperature, while the weather

[‡]The remaining sample also includes non-public sector firms in which the government may hold a majority stake.

data from 2004 to 2013 are used to match the financial data from 2005 to 2014. We use lagged one-year period weather data for regression analysis.

The E-OBS uses a regular latitude-longitude grid projection, and all weather variables have a resolution at the 0.1° by 0.1° level. The details of mapping weather grids to firm locations can be found in the appendix. The raw database is large, as it includes 14,600 days, and 705 longitude and 465 latitude points. There are approximately 4.8 billion daily weather observations. Since our financial data are annual, we first transform our weather variables of interest from daily to yearly. The mean temperature trend in Europe, using all E-OBS data from 1950 to 2014, is plotted in Figure 1. The fitted trend line reveals a clear upward trend in the yearly mean temperature in the European continent, with an increase of 2.11°C (0.033*64) from 1950 to 2014. This is in agreement with data reported by the European Environment Agency, which shows an average increase of mean near-surface temperature in Europe of between 1.94°C and 1.99°C over the last decade, relative to preindustrial levels.[§] The majority of the change occurs after 1950.

The main explanatory variables in our regressions are defined as follows:

- **Mean temp**: the average daily mean temperatures in a year at each location on the weather grid.
- **Anomaly**: the difference between the current year's *Mean temp* and the

[§]See https://www.eea.europa.eu/ims/global-and-european-temperatures for details.

average *Mean temp* computed over the previous 30 years. This measure reflects the deviations of the current *Mean temp* from its past long-run average.

- **Days above 30**: the total number of days above 30°C in a year at each location.

- **Days above 90th**: a relative measure of hot days in a year and a given firm location, taking into account the frequency of abnormally high temperatures recorded in each month at that location. To compute this variable, we consider the *maximum* daily temperature distribution in any given month/location, derived from historical data for 1974–2003. We then count the number of days in each month/location over the sample period (2004–2014) that have exceeded the 90th percentile of the *maximum* temperature distribution for that month. Finally, we add together all the days that exceeded the 90th percentile across all the months in the year of interest for each firm location.

- **Days above 90th & 30**: the number of days on which the daily *maximum* temperature was above the 90th percentile of the daily *maximum* temperatures and above 30°C.

We also define cold-day measures such as "Days below 0", "Days below 10th", and "Days below 10th and 0". These are used as additional control variables when studying the hot temperature effects.

Once we obtain the yearly weather variables at each cell over the weather grid, we match these weather cells with the coordinates of the postcodes of each firm's address. We use Python's *Pgecode* package to convert each firm's headquarter postcode into a longitude and a latitude. We then match the weather grids to the firms' locations. The matching is highly accurate, and the average distance between a firm's location and the centre of a matched weather grid is within 5km.

Our dependent variable is the ratio of operating income to EBITDA. Both operating income and EBITDA are scaled by the total assets in the same year. We also collect the log value of total asset, firm age, ratio of cash holdings over total assets, and interest coverage ratio to calculate the financial-constraint measures: FCP score (Schauer et al. (2019)) and SA score (Hadlock and Pierce (2010)).

4.2.2 Summary statistics

Table 4.1 reports the sample distribution across the European continent. Our sample includes Europe's largest national economies, such as Germany, France, the United Kingdom, Italy, Spain, and the Netherlands. As both southern and northern Europe countries are represented, we are able to consider a wide range of weather conditions and fluctuations over time. Italy and France together contribute almost half of the firm-year observations, with 25.07% and 25.13%, respectively. Switzerland has the smallest number of observations (998).

Table 4.2 presents the distribution of industries in our sample, following the Orbis NACE classification. The wholesale, manufacturing, and construction industries have the largest numbers of firms, accounting for 30.08%, 18.91%, and 15.25% of the total firm-year observations, respectively.

Table 4.3 summarises the firm-level financial ratios. All the variables are winsorised at the 1% and 99% levels. As we can see, the mean values of operating income and EBITDA are 5.8% and 9.5%, respectively. The average log value of the total assets of the firms in our sample is 7.29, which equates to approximately 1.5 million Euros. The average firm age is 16.8 years.

To illustrate the global warming trend in Europe, Table 4.4 shows temperature anomalies over time. Temperature anomalies tell us by how much the mean temperature in a year deviates from its past long-run value. Table 4.4 illustrates that, in 8 of the 10 years in the sample period, temperatures were abnormally warm. For example, the weather anomaly in 2011 was 0.85°C higher than in the previous 30 years. Figure 4.2 shows a temperature-anomaly heat map, year by year across the European continent, using raw weather data from E-OBS. The majority of the European continent is coloured red in each year, meaning that the global warming trend holds not only at the aggregate level but also in most locations across Europe.

Table 4.5 presents the summary statistics of our temperature variables. The average yearly mean temperature in our sample is 12.52°C, and the standard deviation is 3.48°C. In Europe, there are 28 days above 30°C and 48 days below 0°C in an average year. Assuming the weather distribution at each location never changes over time, there should be 36.5 days above the 90^{th} or below the 10^{th} percentiles, with 18.25 days above the 95^{th} or below the 5^{th} percentiles. In reality, we observe more extreme hot days (54.15 at the 95^{th} percentile and 31.09 at the 90^{th} percentile) and fewer extreme cold days (29.77 at the 5^{th} percentile and 15.05 at the 10^{th} percentile) than expected, both of which clearly point to global warming.

Table 4.6 shows the mean values of various temperature measures for different countries. We see that Spain has the highest mean temperature (15.72°C) and largest number of days above 30°C in a year (54.01). Finland has the lowest mean temperature (5.18°C), while Denmark has the smallest number of days above 30°C in a year (0.37). It is worth noting that the above statistics describe temperatures at the locations of the firms in our sample. This means that they indicate average conditions in the most densely populated areas and not necessarily the average temperatures across the countries' respective territories.

4.3 Methodology

To test the relationship between the firms' profitability and temperature shocks, we run regressions of firm-level profitability on various temperature-exposure proxies. Firm profitability is measured as operating income over total assets.

We follow Dell et al. (2012) and Dell et al. (2014) and use panel regression as our baseline model. Standard errors are two-way clustered at the firm level and country-year level (Baum et al. (2010)), as they are more robust than single clustering in this setting (Addoum et al. (2020)), and two-way clustered standard errors are more robust than standard errors clustered at the firm level or adjusted for spatial correlations in this setting. The model is as follows:

$$Operating\,Income_{i,j,t} = \theta_i + \theta_{j,t} + \rho T_{i,t-1} + \gamma P_{i,t-1} + \epsilon_{i,j,t} \tag{4.1}$$

Equation 4.1 is our baseline model, where i,j,t are the indices for firm i, industry j, year t. Explanatory variables include a temperature exposure variable $T_{i,t-1}$ and a precipitation exposure variable $P_{i,t-1}$. Controlling for precipitation is due to the historically correlation between temperature and precipitation in the same location (Auffhammer et al. (2013)). We control for firm fixed effects θ_i and industry by year fixed effects $\theta_{j,t}$.

It is difficult to tell which firm-specific controls, such as accounting ratios, would be affected by temperature exposure. If they are affected, their inclusion in the regression alongside our temperature variables would prevent us from measuring the true impact of temperature on the firm's profitability. In this case, firm-specific covariates could be "bad controls", as observed by Angrist and Pischke (2009). For this reason, we do not employ firm-level time-varying controls in our regressions, in line with Addoum et al. (2020). We control for precipitation, as the profitability of some industry sectors can be influenced by both temperature and rainfall (e.g., the agriculture and water utility sectors). We lag our weather variables to ensure that there are no lead effects due to the different reporting dates of the firms in our sample. For example, for many firms, the reporting date is 31 March. In that case, it would be inappropriate to use average weather temperatures over that year. As a robustness check, we also estimate panel regression with contemporaneous weather variables, and the results hold.

4.4 Results

4.4.1 Baseline estimates

Table 4.7 presents the results of the baseline regression. We find that temperature exposure has a significant impact on operating income in all seven specifications shown in the table. Model 1 shows the estimate for Mean temp and indicates that a 1°C mean temperature increase will lead to a highly statistically significant 0.393% drop in the ratio of operating income to total assets, representing a decline of 6.8% relative to the ratio's mean value (5.8%) reported in Table 4.3. This is an economically significant loss for a firm. In model 3, we investigate the impact of the number of hot days above 30°C. On average, Operating income will fall by 5.3%, relative to its mean value, for a one standard deviation (28.08 days) increase in hot days above 30°C. However, this result is only statistically significant at the

10% level.

People living at different latitudes may have different perceptions of the same temperature. For example, people in Spain may not consider 30°C to be a very high temperature, while people in Finland probably would. Thus, in model 5, we investigate relative extreme temperature exposure, defined as a maximum temperature above the 90^{th} percentile value. Here, an extreme hot temperature is defined according to the historical maximum temperature distribution at the same location, month by month. Our results show that a one standard deviation increase in the number of hot days above the 90^{th} percentile will cause *Operating income* to decrease by 0.141% (significant at 5% level), which is equivalent to a 2.4% drop in the *Operating income* sample mean value.

In model 7, we use the strictest definition of extreme hot days. A "hot day" was defined as one with a maximum temperature above both 30°C and the 90^{th} percentile value. This isolate the effect on operating income of particularly hot months. Unsurprisingly, the magnitude of the coefficient of this variable is similar to that of the coefficient of days above 30°C.

Our research aligns with the broader literature on the negative effects of hot weather on firm performance, as reported by studies like Addoum et al. (2023), Pankratz et al. (2023), Pankratz and Schiller (2021), Custodio et al. (2022). A key observation from Pankratz et al. (2023) is a 0.003% decrease in quarterly operating income to total assets for each additional hot day, closely paralleling our own finding of a 0.011% annual decrease in operating income ratio—a figure that closely matches the compounded effect of quarterly impact of Pankratz et al. (2023) over a year.

However, our study reveals a more pronounced economic impact of climate change compared to some literature, such as Addoum et al. (2020), who found no significant effects of hot weather on the profitability of large US corporations. This discrepancy highlights the differences in climate change impact between small and large firms. Small businesses, often constrained in resources and lacking comprehensive insurance coverage, face greater challenges in adapting to climate change compared to their larger counterparts (Berkhout et al. (2006); Hoffmann et al. (2009))). The lack of diversification in operations and geographical spread makes SMEs more vulnerable to localized climate risks. Furthermore, small and micro firms may struggle to fully understand and mitigate complex climate risks (Weinhofer and Busch (2013)).

4.4.2 Financial Constraints

In comparison with large corporations, small firms may be less able to face extreme weather due to their reduced ability to redistribute resources away from the affected areas (Custodio et al. (2022)). If size is a determining factor of weather vulnerability, we should observe a differential impact of temperature exposure between small firms and micro firms, with the latter being more affected.

We proceed with our analysis by extending our baseline models, interacting the temperature-exposure variables with a firm-size dummy to identify the micro firms. The results are reported in Table 4.8. We find a statistically significantly negative impact for all interacted terms across all regression specifications. The mean temperature data reveal that micro firms' operating income shrinks by 35.10% more than that of small firms (0.119%/0.339%). In relation to absolute and relative hot days, we observe that small businesses are not significantly affected. This suggests that the negative and mildly statistically significant effects observed in Table 7 for the whole sample is due to the negative influence of temperate exposure on micro firms' profitability. Indeed, the coefficients of the temperature variables interacted with the micro dummy in Table 4.8 are highly statistically significant and 2–3.5 times larger than the coefficients of the hot day variables in Table 4.7.

Another channel through which temperature may influence operating income is a firm's ability to access sources of financing. This is because financially constrained companies may lack the resources to mitigate climate risk and recover swiftly when affected by major weather events. As before, we test this hypothesis by interacting temperature-exposure variables with a dummy that captures financial constraints at the firm level. To identify financially constrained firms, we adopt the financial constraint indicator (FCP) proposed by Schauer et al. (2019), using a large sample of private European firms. We employ a dummy that denote as financially constrained (dummy value = 1) those firms with an FCP score in the top 20% of the score distribution. The score is the weighted average of firm size, return on assets, cash holdings, and interest coverage. The severity of the financial constraints for a firm increases with the score and is inversely correlated with the above factors.

The results reported in Table 4.9 show that, in all the regression specifications, a statistically significant negative effect is found for the interaction term of the financial-constraint dummy and for each of the temperature-exposure measures. Regarding the mean temperature, both baseline and interaction terms have statistically significant negative coefficients. Compared with unconstrained firms, financial constrained ones suffer an additional 65.5% (0.163%/0.249%) contraction in operating income in warmer weather. Looking at the extreme hot days measures, we find only the interaction term to be statistically significant, which suggests that only financially constrained firms have suffered due to absolute or relative hot days. The fall in average operating income triggered by a one standard deviation change in hot day measures varies between 12% and 18%, depending on the measure.

We find a similar pattern when looking at the financial constraints on small and micro firms separately, as shown in Tables 4.B.1 and 4.B.2 in the Appendix.

4.4.3 Owner-Manager

In this section, we investigate the role of corporate ownership in the effect of temperature exposure on firm profitability. To do so, we restrict the sample to firms in the Orbis database that have available information in the "global ultimate owner" (GUO) field. The GUO is the entity (corporation, individual, family, or government) who owns – directly or indirectly – a proportion of a firm's equity greater than a specific threshold. Researchers can choose one of two thresholds: 25.01% or 50.01%. We opt for 50.01%, a figure which implies that the GUO has full control of the firm.

Following Kalemli-Ozcan et al. (2015) and using the owner definitions in Orbis, we identify four types of owner: "Industrial" owners, which are non-financial corporations or owners falling in the "employees/managers/directors" group in Orbis and believed to bring similar "expertise" as non-financial corporate owners; "Family" owners, who are one or more named individuals or families who belong to the "Family investor" group in Orbis; "Financial" owners, which are companies in the "Financial investor" group; and "Government" owners, which are public authorities (state or government). Finally, firms for which it is not possible to identify the ultimate owner are classed as "Other".

Table 4.10 reports results for the baseline model augmented with ownership type dummies interacted with temperature-exposure variables. We find that, for firms controlled by families or the government, the negative impact on profitability of increases in mean temperature are partially (families) or fully (government) neutralised. Indeed, for government owners, the overall impact is positive. For industrial and financial owners, the coefficient of the interaction term is not significant, which implies that firms in this category suffer a reduction in operating income with warmer climate, in line with the baseline findings. Our results are in line with Gentry et al. (2016), who document the long-term orientation and higher risk aversion of family-owned businesses. We conjecture that this could lead to greater efforts to mitigate climate-change risk, which would make family-owned firm more resilient to higher temperatures. Similarly, as government-controlled firms are known to be more risk averse than other types of firm (Boubakri et al. (2013)), it is not surprising to see that they are better able to face the effects of climate change and hence show greater endurance to a warmer environment. Table 4.10 shows some evidence that family- and government-owned firms are also less vulnerable to relative hot days. The same result is not observed for absolute hot days.

We further investigate whether the impact of weather conditions on a firm's performance could be influenced by the extent of the "agency problem" between owners and the firm management. When owners are also managers, they have an increased exposure to firm-specific risk because they have invested both their wealth and their own human capital in the firm. This is likely to decrease their risk tolerance (Brisley et al. (2021)) which, as for family-owned companies, may generate incentives to mitigate climate risk. Our findings in Table 4.11 support this conclusion. In the table, we use the baseline model with temperature variables interacted with a dummy which identifies whether the GUO is a current manager. In our sample, -35.82% of the GUOs are also current managers of the firms. As shown in the Table 4.11, the negative impact of mean temperature on profitability is significantly reduced if the GUO is also a current manager.

4.4.4 Industry Effects

Weather's heterogeneous impact across industries has been documented in several studies. Addoum et al. (2023) show that over 40% of US industries are significantly affected, positively or negatively, by temperature shocks. Industry-related sensitivity to heat is also found by Pankratz et al. (2023), Custodio et al. (2022), and Graff Zivin and Neidell (2014).

Arising from this is the question of whether the heterogeneous industry effects observed in large firms can also be observed in small businesses. We analysed the industries represented in our sample individually and, as in previous literature, found heat sensitivities. In Tables 4.12 and 4.13, we illustrate two such cases in which industry-specific dummies interacted with temperature variables and show statistically significant coefficients. In Table 4.12, we look at the energy and utilities sectors. Here, the interaction term has a significantly positive effect for both mean temperature and the relative hot days measure. The interaction coefficient is larger than that of the reference base group, which indicates that warmer weather does not cause these sectors to become less profitable. This may be because the more extreme weather conditions caused by global warming require more energy for both cooling and heating systems in private and commercial properties. Indeed, a recent article in Science (Cohen et al. (2021)) argues that warming in the Arctic can be linked to extreme cold weather in parts of North America and Asia.

We test the agriculture industry separately. Table 4.13 shows that hot days, both absolute and relative, can produce a positive and statistically significant impact on the profitability of agricultural firms. However, the interaction of the agriculture sector dummy and mean temperature is not significant. This ambiguity in our findings is not surprising. As noted by Kim (2012), the effect of global warming on agriculture can be positive or negative, depending on a number of factors. A warmer climate and higher levels of carbon dioxide in the atmosphere can increase crop yields as the cultivation period expands and CO2 acts as a fertiliser. Higher temperatures can also reduce the damage done by low temperatures to winter crops. By contrast, extremely high temperatures can reduce the quantity and quality of crops (partly due to an increase in weeds and pests) and reduce land fertility due to soil erosion caused by heavy rains and floods. Some areas may be disadvantaged by extreme heat, while others closer to the pole or at higher altitudes may benefit from warmer weather.

The analysis of weather's heterogeneous impact across industries highlights how SMEs operating in certain sectors can potentially benefit from climate change, specifically higher temperatures. This is notably observed in the energy and utilities sector and the agriculture industry, as detailed in the study.

In the energy and utilities sector, the interaction term with temperature variables indicates a significantly positive effect, suggesting that warmer weather does not reduce profitability in these industries. This phenomenon can be attributed to the increased demand for energy, both for cooling systems during hotter periods and heating systems in response to extreme cold events linked to global warming, as suggested by Cohen et al. (2021). Extreme weather conditions, whether hot or cold, tend to increase energy consumption in residential and commercial properties, potentially boosting the profitability of firms in this sector.

The agriculture industry presents a more complex picture. The study finds that hot days, both absolute and relative, can positively impact agricultural firms' profitability, though the interaction with mean temperature is not significant. This ambiguity reflects the dual nature of climate change's impact on agriculture. On one hand, a warmer climate and higher CO2 levels can extend the cultivation period and act as a fertilizer, increasing crop yields. This benefit is particularly pronounced for winter crops that are vulnerable to low temperatures. On the other hand, extreme heat can negatively affect crop quantity and quality, increase pests and weeds, and lead to soil erosion due to heavy rains and floods.

Consequently, the net effect of global warming on agriculture varies based on geographical location, crop type, and local climate conditions.

These findings underscore the importance of industry-specific analysis in understanding the impact of climate change on business profitability. While certain industries like energy and utilities may experience increased demand and profitability due to extreme weather conditions, others like agriculture face a nuanced scenario where benefits are contingent on various factors. This understanding is crucial for businesses and policymakers in these sectors to develop strategies that maximize potential benefits while mitigating the adverse effects of climate change.

4.5 Robustness

We run a series of tests to check the robustness of our findings. We used the 95^{th} percentile as an alternative threshold for the relative hot days. Unreported results confirm our main findings.

We define financially constrained firms using the SA index proposed by Hadlock and Pierce (2010). One advantage of the SA index is that its construction only requires firm size and age, which are available for most of the firms in our sample. Furthermore, the SA index does not require lagged firm information, as all the variables used to derive it are contemporaneous with the dependent variable. This enables us to increase considerably the number of observations available for estimation. Table 4.B.3 presents the results when the SA financial-constraint dummy is employed. The results are qualitatively unchanged in relation to those of the FCP index reported in Table 4.9.

Tables 4.B.4 and 4.B.5 report the results for the SA financial-constraint dummy in the small and micro firms' subsamples, respectively. The results are consistent with those obtained with the FCP score, with the exception of the interaction with hot days measures also being significantly negative. Nevertheless, the results consistently indicate that financially constrained firms are more negatively affected by hot temperature.

In the unreported results, we use EBITDA – rather than operating income – as a profitability measure. Our main findings remain largely unchanged.

4.6 Conclusions

In this paper, we study the effect of increasing temperatures on the performance of small and micro European enterprises. Small businesses' operations are more geographically localised than those of large firms. Thus, we can more easily establish a link between their performance and changes in temperature. Combing a large European dataset from Orbis and high-resolution weather data from E-OBS, we find a significant negative impact of hot weather on corporate profitability.

We investigate several economic channels through which temperature shocks could affect firm performance. Specifically, we investigate whether financially constrained firms and micro firms are more severely affected by temperature shocks than other firms. We observe that the negative impact of hot temperatures was much stronger for financially constrained firms. We also find that micro firms suffered more from hot weather than small firms did.

We find heterogeneous effects of global warming across industries. Unsurprisingly, the energy sector did not suffer due to extremely hot weather, thus exhibiting a unique pattern amongst the industries. Finally, our results suggest that family and government ownership can mitigate the negative effects of hot weather.

Extreme weather events appear to be becoming more frequent and severe. Global warming is likely to generate compounding effects that exacerbate the patterns we have identified in this study and create new ones. Therefore, more research is needed to monitor companies' productivity and ability to survive in a rapidly changing and challenging environment.

For SME decision-makers, this research underscores the urgent need to develop adaptive strategies and resilience against temperature shocks. SMEs, particularly micro firms, are shown to be more vulnerable to these climate-induced impacts, highlighting the importance of climate risk management in their business planning. This may include investing in technologies and processes that mitigate the effects of high temperatures, diversifying their geographical presence, or modifying operational schedules to adapt to temperature changes.

Moreover, the study highlights the role of financial constraints in a firm's ability to withstand climate risks. SMEs with limited access to external finance are more negatively impacted by temperature shocks. This insight is crucial for financial planning and potentially in seeking external funding or government assistance to build resilience against climate change.

Furthermore, the research sheds light on the varied impacts of temperature changes across different industries and ownership structures. Understanding these differential impacts can guide SMEs in strategic decision-making and potential pivots in their business models, especially for those in the more affected sectors.

Overall, the findings of this study serve as a critical wake-up call for SMEs to prioritize climate risk assessment and adaptation in their business strategies. The evidence presented highlights a stark reality: climate change is not just an environmental issue but a direct economic threat to the sustainability and profitability of small and micro enterprises.

4.7 Figures and Tables

Figure 4.1: Mean temperature in Europe from 1950 to 2014

This figure illustrates the mean temperatures in Europe from 1950 to 2014, based on near-surface data from E-OBS. The "mean temperature" is the average daily mean temperature of all areas covered in E-OBS in a year.

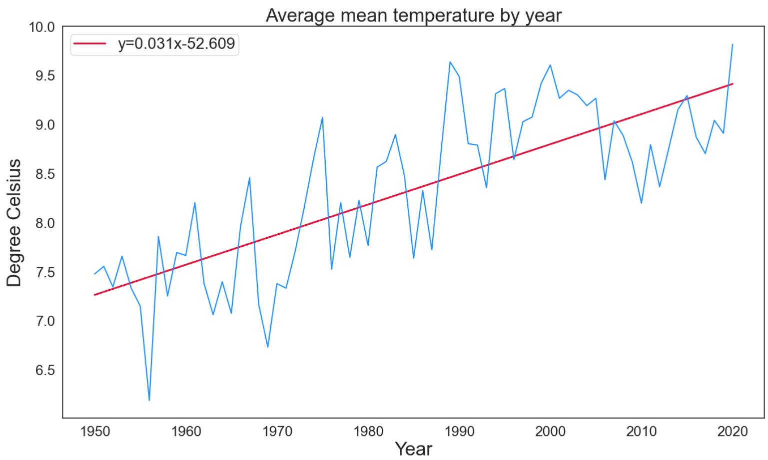


Figure 4.2: Temperature anomaly in Europe by year, 2003–2014

This figure depicts the mean-temperature anomalies across the European continent from 2003 to 2014. A "temperature anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location.

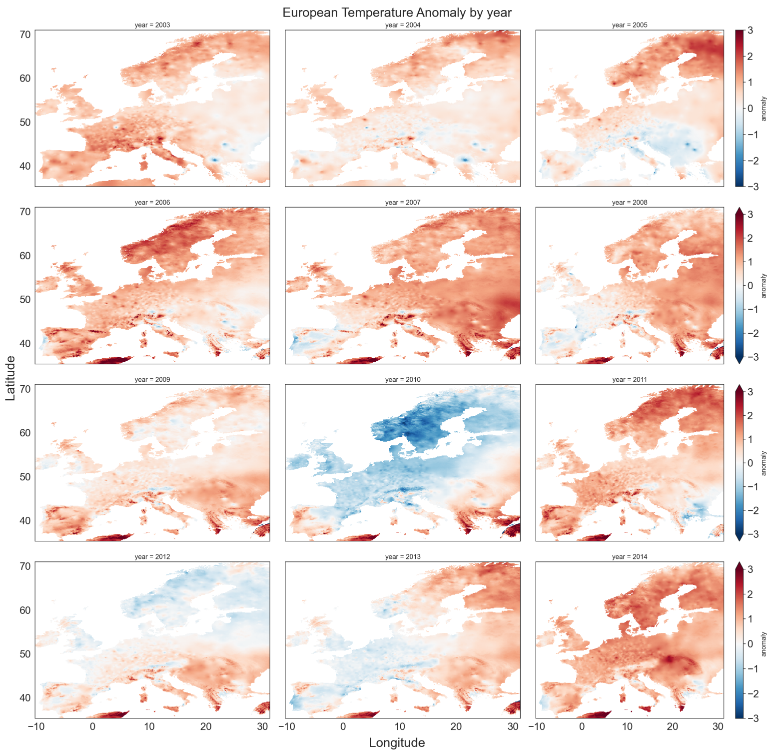


Table 4.1: Country distributions

This table describes the number of small- and micro-firm year observations in our sample. The sample period ranges from 2005 to 2014.

Country	**Firm years**	**Percent**
Austria	19,060	0.27
Belgium	346,752	4.97
Swizerland	998	0.01
Germany	280,704	4.03
Denmark	47,251	0.68
Spain	1,293,461	18.56
Finland	172,082	2.47
France	1,751,750	25.13
United Kingdom	298,345	4.28
Ireland	9,613	0.14
Italy	1,747,565	25.07
Netherland	19,208	0.28
Norway	290,889	4.17
Portugal	323,490	4.64
Sweden	369,655	5.3
Whole sample	6,970,823	100

Table 4.2: Industry distributions

This table shows the industry distribution of firm years in our sample. The industry classifications are according to the NACE Rev. 2 main section in Orbis. The sample period is 2005–2014.

NACE Rev. 2 main section	**Firm years**	**Percent**
Agriculture,forestry and fishing	149,030	2.14
Mining and quarrying	26,611	0.38
Manufacturing	1,318,112	18.91
Electricity,gas,steam and air conditioning supply	44,759	0.64
Water supply;sewerage,waste management and remediation activities	53,209	0.76
Construction	1,063,354	15.25
Wholesale and retail trade;repair of motor vehicles and motorcycles	2,097,156	30.08
Transportation and storage	376,715	5.4
Accommodation and food service activities	296,219	4.25
Information and communication	248,897	3.57
Professional,scientific and technical activities	507,184	7.28
Administrative and support service activities	344,580	4.94
Education	73,626	1.06
Human health and social work activities	209,713	3.01
Arts, entertainment and recreation	86,717	1.24
Other service activities	74,941	1.08
Whole sample	6,970,823	100

Table 4.3: Summary statistics of accounting ratios

This table presents the summary statistics for the financial accounting variables used in our regression analysis. Operating income, EBITDA, and net income are given as ratios of total assets. "Size" is the natural log of total assets. "AGE" is the number of days since incorporation, divided by 365. "Cash holding" is the cash and cash equivalent over total assets. "Interest coverage" is the ratio of EBIT to interest expense. "Financial constraint (FCP)" is the financial-constraint measure from Schauer et al. (2019). "Financial constraint (SA)" is the financial-constraint measure from Hadlock and Pierce (2010). The sample period is 2005–2014.

Variable	**Mean**	**SD**	**P25**	**P50**	**P75**
Operating income	0.058	0.149	0.008	0.047	0.112
EBITDA	0.095	0.152	0.029	0.081	0.158
Net income	0.034	0.124	0.000	0.023	0.079
Size	7.292	1.075	6.570	7.361	8.110
Age	16.812	13.507	6.844	13.849	22.858
Cash holding	0.149	0.180	0.016	0.075	0.219
Interest coverage	27.016	101.873	0.886	3.267	14.647
Financial constraint (FCP)	-1.911	2.792	-1.948	-1.275	-0.998
Financial constraint (SA)	-3.711	0.599	-4.001	-3.614	-3.309

Table 4.4: Temperature anomaly by year

This table presents the summary statistics for temperature anomalies by year. A "temperature anomaly" is the difference between the yearly mean temperature and the average mean value of the previous 30 years, measured in degrees Celsius (°C).

Year	**Mean**	**Median**	**Min**	**Max**
2004	0.396	0.352	-1.445	2.619
2005	0.302	0.342	-1.950	2.218
2006	0.841	0.942	-1.640	4.987
2007	0.611	0.697	-1.861	4.077
2008	0.319	0.212	-4.492	3.483
2009	0.454	0.402	-1.215	4.266
2010	-0.588	-0.688	-2.844	3.494
2011	0.853	0.904	-1.532	4.011
2012	0.184	0.113	-1.670	3.290
2013	-0.056	-0.136	-2.268	2.562
2014	0.971	1.023	-1.035	3.085
Whole sample	0.329	0.351	-4.492	4.987

Table 4.5: Summary statistics of temperature exposures

This table provides the summary statistics for the weather variables used in our regression analysis. "Mean temperature" is the average daily mean temperature over the year. A "temperature anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Precipitation" is the average daily precipitation in mm in a year, divided by 100. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days below 0" is the total number of days in a year that saw temperatures below 0°C. "Days above 90^{th} (95^{th})" is the total number of days in a year when the daily maximum temperature was above the 90^{th} (95^{th}) percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days below 10^{th} (5^{th})" indicates the total number of days in a year when the daily minimum temperature in any given month of that year was below the 10^{th} (5^{th}) percentile of the minimum temperature distribution from 1974 to 2003 in the same month. "Days above 90^{th} (95^{th}) and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th} (95^{th})" and "Days above 30°C". "Days below 10^{th} (5^{th}) and 0" are the total number of days in a year when the daily minimum temperature met the conditions of both "Days below 10^{th} (5^{th})" and "Days below 0°C". The sample period is 2005–2014.

Variable	**Mean**	**SD**	**p25**	**p50**	**p75**
Mean temperature	12.52	3.48	10.57	12.70	14.99
Temperature anomaly	0.33	0.65	-0.07	0.35	0.81
Precipitation (mm/100)	7.34	3.05	5.37	6.92	8.63
Days above 30	27.86	28.08	4.00	18.00	46.00
Days above 90^{th} pctl	54.51	20.19	40.00	51.00	65.00
Days above 95^{th} pctl	31.09	14.92	21.00	29.00	38.00
Days above 90^{th} pctl & 30	13.68	12.31	3.00	11.00	21.00
Days above 95^{th} pctl & 30	9.22	8.82	2.00	7.00	14.00
Days below 10^{th} pctl	29.77	17.26	18.00	27.00	38.00
Days below 5^{th} pctl	15.05	11.24	7.00	13.00	20.00
Days below 10^{th} pctl & 0	14.17	11.67	5.00	13.00	20.00
Days below 5^{th} pctl & 0	8.12	7.76	2.00	6.00	12.00
Days below 0	48.39	42.55	15.00	41.00	68.00

Table 4.6: Temperature by country

This table provides summary statistics for temperature by country. "Mean", "Max", and "Min" are, respectively, the average daily mean and the maximum and minimum temperatures over the sample period. "Anomaly" is the average difference between "Mean" and the average mean temperature of the past 30 years in the same location over the sample period. The sample period is 2005–2014.

Country	**Mean**	**Max**	**Min**	**Anomaly**	**Days above 30**	**Days below 0**
Austria	9.52	14.20	5.27	0.15	12.54	96.50
Belgium	10.66	14.68	6.87	0.29	4.76	50.12
Swizerland	7.72	12.15	3.78	0.25	5.13	116.09
Germany	9.74	14.11	5.43	0.30	7.99	77.90
Denmark	8.80	11.62	6.05	0.00	0.37	72.27
Spain	15.72	21.00	10.55	0.32	54.01	19.11
Finland	5.18	8.86	1.50	0.71	0.92	147.51
France	12.05	16.60	7.67	0.26	15.54	46.49
United Kingdom	10.43	14.24	6.68	0.28	1.05	40.98
Ireland	10.37	13.57	7.19	-0.03	0.00	26.00
Italy	14.37	19.23	9.86	0.44	45.00	37.28
Netherland	10.26	14.20	6.07	0.15	3.31	59.25
Norway	5.89	9.53	2.65	0.39	0.48	127.27
Portugal	15.71	21.30	11.21	-0.05	41.11	5.98
Sweden	7.06	10.90	3.35	0.43	0.96	117.59
Whole sample	12.52	17.16	8.13	0.33	27.86	48.39

Table 4.7: The impact of temperature on firm profitability

This table reports the estimated coefficients for the OLS regression of equation 4.1. The dependent variable is Operating income over total assets. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 3, 5, and 7, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean temp	-0.00393***						
	[-3.251]						
Days above 30		-0.00010*	-0.00011*				
		[-1.678]	[-1.950]				
Days above 90^{th} pctl				-0.00008**	-0.00007**		
				[-2.512]	[-2.164]		
Days above 90^{th} pctl& 30						-0.00010	-0.00011*
						[-1.525]	[-1.876]
Observations	6,970,823	6,970,823	6,970,823	6,970,823	6,970,823	6,970,823	6,970,823
R-squared	0.542	0.542	0.542	0.542	0.542	0.542	0.542
Cold days control	No	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.8: The impact of temperature on the profitability of micro firms

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with the micro-firm dummy. The dependent variable is Operating income over total assets. "Micro TA" equals 1 if the firm is a micro firm in a given year. "Mean temp" is the average daily mean temperature in a year. "Days above 30" are the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00339***			
	[-2.832]			
Mean temp × Micro TA	-0.00119***			
	[-13.083]			
Days above 30		0.00001		
		[0.252]		
Days above 30 × Micro TA		-0.00023***		
		[-8.957]		
Days above 90^{th}			0.00005	
			[1.470]	
Days above 90^{th} × Micro TA			-0.00021***	
			[-13.315]	
Days above 90^{th}&30				0.00010
				[1.599]
Days above 90^{th} & 30 × Micro TA				-0.00039***
				[-8.186]
Observations	6,970,823	6,970,823	6,970,823	6,970,823
R-squared	0.543	0.542	0.543	0.542
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.9: Firm profitability, temperature, and financial constraints

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with the dummy (FCP constraint) that highlights financially constrained firms. The dependent variable is Operating income over total assets. "FCP constraint" equals 1 when it is in the top 20% for its Schauer et al. (2019) score. "Mean temp" is the average daily mean temperature in a year. "Days above 30" are the total number of days in a year that saw temperatures above 30 °C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00249**			
	[-2.593]			
Mean temp × FCP constraint	-0.00163***			
	[-9.984]			
Days above 30		0.00001		
		[0.284]		
Days above 30 × FCP constraint		-0.00037***		
		[-7.775]		
Days above 90^{th}			0.00002	
			[0.820]	
Days above 90^{th} × FCP constraint			-0.00034***	
			[-9.213]	
Days above 90^{th} & 30				0.00008
				[1.410]
Days above 90^{th} & 30 × FCP constraint				-0.00080***
				[-7.575]
Observations	4,215,177	4,215,177	4,215,177	4,215,177
R-squared	0.580	0.579	0.580	0.579
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.10: Ownership structure

This table reports the estimated coefficients for the OLS regression of equation 4.1, with the temperature variables interacted with different firm owner dummies. The dependent variable is Operating income over total assets. "Industrial" is a dummy that equals 1 if a firm's ultimate owner is a non-financial company. "Family" is a dummy that equals 1 if a firm's ultimate owner is an individual or a family. "Financial" is a dummy that equals 1 if a firm's ultimate owner is a financial company. "Government" is a dummy that equals 1 if a firm's ultimate owner is a government authority. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00488***			
	[-3.240]			
Mean temp × Industrial	0.00032			
	[0.264]			
Mean temp × Family	0.00291**			
	[2.185]			
Mean temp × Financial	0.00166			
	[1.159]			
Mean temp × Government	0.00607**			
	[2.092]			
Days above 30		-0.00014**		
		[-2.183]		
Days above 30 × Industrial		0.00004		
		[0.623]		
Days above 30 × Family		0.00008		
		[1.242]		
Days above 30 × Financial		0.00007		
		[1.134]		
Days above 30 × Government		0.00001		
		[0.045]		
Days above 90^{th}			-0.00011**	
			[-2.586]	
Days above 90^{th} × Industry			0.00005	
			[1.159]	
Days above 90^{th} × Family			0.00011**	
			[2.248]	
Days above 90^{th} × Financial			0.00009*	
			[1.776]	
Days above 90^{th} × Government			0.00022**	
			[2.009]	
Days above 90^{th}&30				-0.00014*
				[-1.972]
Days above 90^{th}&30 × Industry				0.00002
				[0.251]
Days above 90^{th}&30 × Family				0.00008
				[0.900]
Days above 90^{th}&30 × Financial				0.00007
				[0.811]
Days above 90^{th}&30 × Government				-0.00002
				[-0.110]
Observations	6,970,823	6,970,823	6,970,823	6,970,823
R-squared	0.542	0.542	0.542	0.542
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.11: Manager-owner

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with global ultimate owner (GUO) manager dummies. The dependent variable is Operating income over total assets. "GUO manager" is a dummy that equals 1 if a firm's GUO is also a current manager of the firm. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution from 1974 to 2003 in the same month. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00364***			
	[-3.158]			
Mean temp × GUO manager	0.00231**			
	[2.466]			
Days above 30		-0.00009*		
		[-1.683]		
Days above 30 × GUO manager		0.00004		
		[1.070]		
Days above 90^{th}			-0.00006*	
			[-1.692]	
Days above 90^{th} × GUO manager			0.00006*	
			[1.828]	
Days above 90^{th}&30				-0.00010*
				[-1.781]
Days above 90^{th}&30 × GUO manager				0.00006
				[1.492]
Observations	3,455,246	3,455,246	3,455,246	3,455,246
R-squared	0.551	0.551	0.551	0.551
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.12: Energy and utility sectors

This table reports the estimated coefficients for the OLS regression of equation 4.1, with the temperature variables interacted with the energy-utility dummy. The dependent variable is Operating income over total assets. The energy-utility dummy is equal to 1 if the firm is operating in either the energy or the utility sector. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution from 1974 to 2003 in the same month. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year foxed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00399***			
	[-3.269]			
Mean temp × Energy Utility	0.00446**			
	[2.522]			
Days above 30		-0.00011*		
		[-1.969]		
Days above 30 × Energy Utility		0.00013		
		[1.499]		
Days above 90^{th}			-0.00007**	
			[-2.210]	
Days above 90th × Energy Utility			0.00016***	
			[2.809]	
Days above 90^{th}&30				-0.00012*
				[-1.912]
Days above 90^{th}&30 × Energy Utility				0.00022**
				[2.171]
Observations	6,970,823	6,970,823	6,970,823	6,970,823
R-squared	0.542	0.542	0.542	0.542
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.13: The Agriculture Sector

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with the agriculture dummy. The dependent variable is Operating income over total assets. The agriculture dummy equals 1 if the firm is operating in the "Agriculture, forestry, and fishing" industry. The dependent variable is "Operating income". "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00396***			
	[-3.205]			
Mean temp × Agriculture	0.00095			
	[0.543]			
Days above 30		-0.00011**		
		[-1.980]		
Days above 30 × Agriculture		0.00014*		
		[1.879]		
Days above 90^{th}			-0.00007**	
			[-2.207]	
Days above 90^{th} × Agriculture			0.00011**	
			[2.201]	
Days above 90^{th}&30				-0.00012*
				[-1.921]
Days above 90^{th}&30 × Agriculture				0.00019**
				[2.003]
Observations	6,970,823	6,970,823	6,970,823	6,970,823
R-squared	0.542	0.542	0.542	0.542
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Appendices

4.A Mapping Firm locations and Weather grids

- Geocoding the headquarter postcode of each firm to obtain the longitude and latitude of the headquarter using *pgeocode* library in Python.
- The longitude and latitude of each firm will be mapped to the center coordinate of the weather grid in E-OBS dataset. The weather variable grids cover the area: 25N-71.5N $\times$ 25W-45E. The resolution is 0.1 degree by 0.1 degree. There are 705 longitudes and 465 latitudes in the covered area. Note: The area of the grid will not be a rectangular box with a fixed width and length. Typically, the area is larger for grids near the equator. The 0.1 degree by 0.1 degree grid box area at the latitude of 71.5 °N is around 3.49 km $\times$ 11.1 km, while the grid box area at the latitude of 25 °N is around 10.26km $\times$ 11.1km.

  Take 71.5 °N for example. The Earth's circumference at a given latitude can be found using the following formula: $C = 2\pi r \times cos(latitude)$, where

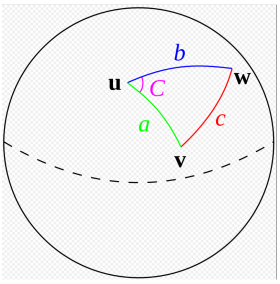
C is the circumference, r is the Earth's radius (approximately 6,371 km), and latitude is in radians.

- Convert the latitude to radians: $71.5 \times \frac{\pi}{180} = 1.247$ radians.
- Calculate the circumference at 71.5°N: $C = 2\pi \times 6371 km \times cos(1.247) =$ 1256.24
- Find the distance of 1 degree of longitude: 12,565.24 km / 360° = 34.90 km/degree.
- Finally, calculate the distance for 0.1 degree of longitude: 34.90 km/degree × 0.1° = 3.49 km.

At a latitude of 71.5°N (or 71.5°S), 0.1 degree of longitude is approximately 3.49 kilometers. The distance for 0.1 degree of latitude remains about 11.1 km, as the distance between lines of latitude does not change with latitude. *Mean temp* and the rolling average of the yearly mean temperature *Mean temp* over the previous 30 years.

- We use the ball tree module from the Scikit-learn library to efficiently find the latitude and longitude neighbors. First, we have one data frame of firms' longitudes and latitudes from step 1. Second, we have another data frame of weather grids' longitudes and latitudes from step 2. The idea is to loop through the weather grid's data frame to find the nearest weather grid coordinate for each firm according to the nearest earth surface distance rule.

The haversine metric used in the ball tree is the angular distance between two points on the surface of a sphere. The first coordinate of each point is assumed to be the latitude, and the second is the longitude, given in radians. The dimension of the data must be 2.



Given a unit sphere, a "triangle" on the surface of the sphere is defined by the great circles connecting three points u, v, and w on the sphere. If the lengths of these three sides are a (from u to v), b (from u to w), and c (from v to w), and the angle of the corner opposite c is C, then the law of haversines states: $hav(c) = hav(a - b) + sin(a)sin(b)hav(c)$, where $hav(\theta) = \sin^2 \frac{\theta}{2}$.

The nearest distance formula translated to longitude and latitude radians:

$$D(x, y) = 2arcsin\left[\sqrt{sin^2(\frac{x1 - y1}{2}) + cos(x1)cos(y1)sin^2(\frac{x2 - y2}{2})}\right]$$

- After the mapping, the average distance between the firm coordinate and the weather grid coordinate is 4.4 km, we also drop the observations where the nearest distance is above 10km.

4.B Figures and Tables

Table 4.B.1: Financial constraints in small firms

This table reports the estimated coefficients for the OLS regression of equation 4.1, with the temperature variables interacted with the FCP constraint dummy. The dependent variable is Operating income over total assets. The sample is limited to small firms only. "FCP constraint" equals 1 if the firm's FCP (Schauer et al. (2019)) score is in the top 20% of the sample distribution of FCP scores. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00186**			
	[-2.323]			
Mean temp × FCP constraint	-0.00145***			
	[-8.765]			
Days above 30		-0.00001		
		[-0.278]		
Days above 30 × FCP constraint		-0.00031***		
		[-6.327]		
Days above 90th			0.00001	
			[0.453]	
Days above 90th × FCP constraint			-0.00032***	
			[-8.625]	
Days above 90th & 30				0.00004
				[0.988]
Days above 90th & 30 × FCP constraint				-0.00070***
				[-6.927]
Observations	1,701,932	1,701,932	1,701,932	1,701,932
R-squared	0.652	0.651	0.652	0.651
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.B.2: Financial constraints in micro firms

This table reports the estimated coefficients for the OLS regression of equation 4.1, with the temperature variables interacted with the FCP constraint dummy. The dependent variable is Operating income over total assets. The sample is limited to micro firms only. "FCP constraint" equals 1 if the firm's FCP (Schauer et al. (2019)) score is in the top 20% of the sample distribution of FCP scores. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00319***			
	[-2.873]			
Mean temp × FCP constraint	-0.00127***			
	[-8.317]			
Days above 30		0.00001		
		[0.126]		
Days above 30 × FCP constraint		-0.00029***		
		[-6.874]		
Days above 90^{th}			0.00000	
			[0.108]	
Days above 90^{th} × FCP constraint			-0.00026***	
			[-7.582]	
Days above 90^{th} & 30				0.00006
				[0.915]
Days above 90^{th} & 30 × FCP constraint				-0.00062***
				[-6.542]
Observations	2,193,254	2,193,254	2,193,254	2,193,254
R-squared	0.571	0.570	0.570	0.570
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.B.3: Financial constraints – alternative constraint indicator

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with the SA constraint dummy. The dependent variable is Operating income over total assets. “SA constraint” equals 1 if the firm’s SA score (Hadlock and Pierce (2010)) is in the top 20% of the sample distribution. “Mean temp” is the average daily mean temperature in a year. “Days above 30” is the total number of days in a year that saw temperatures above 30°C. “Days above 90^{th}” is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. “Days above 90^{th} and 30” are the total number of days in a year when the daily maximum temperature met the conditions of both “Days above 90^{th}” and “Days above 30°C”. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00407***			
	[-3.385]			
Mean temp × SA constraint	-0.00114***			
	[-18.123]			
Days above 30		-0.00008		
		[-1.468]		
Days above 30 × SA constraint		-0.00018***		
		[-7.446]		
Days above 90^{th}			-0.00003	
			[-0.938]	
Days above 90^{th} × SA constraint			-0.00025***	
			[-15.657]	
Days above 90^{th} & 30				-0.00006
				[-0.907]
Days above 90^{th} & 30 × SA constraint				-0.00039***
				[-7.001]
Observations	6,967,138	6,967,138	6,967,138	6,967,138
R-squared	0.543	0.542	0.543	0.542
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.B.4: Financial constraints in small firms – alternative constraint indicator

This table reports the estimated coefficients for the OLS regression of equation 4.1, with temperature variables interacted with the SA constraint dummy. The dependent variable is Operating income over total assets. The SA constraint equals 1 if the firm's SA score (Hadlock and Pierce (2010)) is in the top 20% of the sample distribution. The sample is limited to small firms only. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year foxed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00301***			
	[-3.122]			
Mean temp × SA constraint	-0.00063***			
	[-8.501]			
Days above 30		-0.00009**		
		[-2.089]		
Days above 30 × SA constraint		-0.00010***		
		[-5.263]		
Days above 90^{th}			-0.00005*	
			[-1.857]	
Days above 90^{th} × SA constraint			-0.00013***	
			[-6.677]	
Days above 90^{th} & 30				-0.00009*
				[-1.906]
Days above 90^{th} & 30 × SA constraint				-0.00027***
				[-5.237]
Observations	2,882,659	2,882,659	2,882,659	2,882,659
R-squared	0.637	0.637	0.637	0.637
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Table 4.B.5: Financial constraints in micro firms – alternative constraint indicator

This table reports the estimated coefficients for the OLS regression of 4.1, with temperature variables interacted with the SA constraint dummy. The dependent variable is Operating income over total assets. The SA constraint equals 1 if the firm's SA score (Hadlock and Pierce (2010)) is in the top 20% of the sample distribution. The sample is limited to micro firms only. "Mean temp" is the average daily mean temperature in a year. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days above 90^{th}" is the total number of days in a year when the daily maximum temperature was above the 90^{th} percentile of the maximum daily temperature distribution of the same month in 1974–2003. "Days above 90^{th} and 30" are the total number of days in a year when the daily maximum temperature met the conditions of both "Days above 90^{th}" and "Days above 30°C". In each specification, we control for precipitation, firm fixed effects, and industry-year foxed effects. In columns 2, 3, and 4, we also control for cold days effects. Robust standard errors, clustered at the firm level and country-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Operating income			
	(1)	(2)	(3)	(4)
Mean temp	-0.00484***			
	[-3.549]			
Mean temp × SA constraint	-0.00090***			
	[-14.777]			
Days above 30		-0.00009		
		[-1.412]		
Days above 30 × SA constraint		-0.00011***		
		[-3.980]		
Days above 90^{th}			-0.00003	
			[-0.779]	
Days above 90^{th} × SA constraint			-0.00020***	
			[-12.632]	
Days above 90^{th} & 30				-0.00006
				[-0.843]
Days above 90^{th} & 30 × SA constraint				-0.00023***
				[-4.000]
Observations	3,963,185	3,963,185	3,963,185	3,963,185
R-squared	0.538	0.538	0.538	0.538
Cold days control	No	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes

Chapter 5

Rain or Shine, Default Risks Align: Exploring the Climate-Default Nexus in Small and Micro Firms

5.1 Introduction

The adverse effects of climate change are being experienced by both individuals and corporations globally. Over the previous three years, devastating flash floods have struck Europe and China, resulting in numerous fatalities and substantial economic damage. Concurrently, extremely hot summers have become a recurring phenomenon. In 2022, unprecedented high temperatures were reported in various European nations and the United States. These drastic weather changes are inextricably tied to global warming. A warmer climate precipitates increased evaporation, leading to higher overall precipitation. Additionally, warmer air is inherently more volatile than cooler air, resulting in more intense rainfall episodes and flash floods. Consequently, the frequency of the events witnessed in Europe and China last year is likely to escalate as global temperatures continue to rise. Given the significant disruption of climate risk on economies, businesses, and livelihoods, climate-related topics have been a key focus of academic research over the past decade. This paper concentrates on the impacts of two chronic climate changes - rising temperatures and increased precipitation risks - on the default probability of companies.

In recent years, a growing body of literature has striven to comprehend the effects of climate change on corporate performance, primarily focusing on large corporations. Utilizing temperature data from the PRISM Climate Group at the establishment level, Addoum et al. (2020) investigated the impact of high temperatures on both the sales and profitability of US public firms. Their approach calculated firm-level temperature exposure through the sales-weighted average of the establishment temperature exposure. Although they observed a slight increase in sales within the energy sector due to lower temperatures and a minor increase in the healthcare industry, their findings did not produce any significant outcomes. Addoum et al. (2023) introduced a novel heat measure by considering the number of hours spent within a given temperature range in a quarter, instead of relying on mean temperature and the number of hot days. Their results revealed heat sensitivity in 40% of US industry sectors. With international data from 93 countries, Pankratz et al. (2023) found that excessively high temperatures can adversely affect both a firm's revenue and profitability, utilizing the headquarter temperature as a proxy for the firm's heat exposure. Custodio et al. (2022) found that a 1°C increase in the daily average temperature corresponds to a 2% decrease in sales for suppliers, based on a paired client and supplier dataset. While the aforementioned studies focused on firm-level temperature exposure, other scholars have employed county-level climate exposures to examine firms' performances. For instance, Javadi et al. (2023) used the PDSI country-level drought intensity to measure climate risk exposure, finding that firms exposed to high climate risk tend to hold more cash reserves. Similarly, Huang et al. (2018) noted that firms located in countries with a high climate risk index are likely to hold more cash for precautionary purposes. Elnahas et al. (2018) found that companies in disaster-prone counties adopt more conservative borrowing strategies compared to those in less vulnerable areas. Nguyen and Phan (2020) used Australia's ratification of the Kyoto Protocol as a quasi-natural experiment to find firms significantly reducing their financial leverage post-ratification, a trend particularly pronounced among financially constrained firms. Whether the observed underperformance of firms due to climate risk will translate into actual default events remains unclear. Our paper aims to fill this research gap. Based on our findings, we contend that climate risk, specifically in the form of rising temperatures and increased precipitation, can elevate firms' default probabilities.

To the best of our knowledge, no extant research has examined the effects of high temperatures or intense precipitation on the actual default events of firms. Predominantly, studies that link climate risk to credit risk at the corporate level concentrate on the pricing of corporate bonds and bank loans. Ehlers et al. (2022), in their investigation of emission-related risks, found that only emissions related to a firm's resources were priced with a significant carbon premium in the global syndicated loan market following the Paris Agreement. The carbon premium applied broadly, extending beyond carbon-intensive industries. Alternatively, Apergis et al. (2022) quantified firm-level climate risk using ESG scores, finding that S&P 500 firms with higher ESG scores exhibited lower bond spreads and superior bond credit ratings between 2010 and 2019. Correa et al. (2020) gauged firm-level physical risk in the U.S. by mapping each firm to country-level natural disaster data from SHELDUS, discovering that banks charged an additional 19 basis points for firms not directly affected by, but at risk of, natural disasters. The authors proposed that the augmented spread resulted from banks' adjustment to the default probability of borrowers, with this elevated loan pricing spread only emerging after climate-related disasters. Huang et al. (2022) explored two distinct firm-level climate risk measures: the first captures perceived climate risk (managerial responses to anticipated physical risks their firms face, sourced from the CDP survey), and the second encapsulates actual climate risk (using natural disaster data from SHELDUS, similar to Correa et al. (2020). They determined that firms exposed to climate risk incurred a surcharge of 42 basis points from banks. Alongside the elevated loan spread demanded by banks for firms experiencing intense drought conditions, Javadi and Masum (2021)) also identified firms with customers exposed to high drought risk (PDSI) as incurring higher spreads. Jung et al. (2018) utilized the CDP survey, finding that firms neglecting to respond to the survey encountered elevated debt costs. Moreover, they discovered that a one standard deviation increase in carbon risk corresponded to a rise in debt cost by 48 to 62 basis points. After accounting for demand-side effects and insurance coverage, Faiella and Natoli (2019) discovered that banks reduced the volume of loans granted to firms exhibiting a high flooding risk in Italy.

The impact of climate risk on sovereign bonds, municipal bonds, and individual mortgage loans has been documented extensively in academic literature. Much of the research pertaining to municipal bonds and mortgages has primarily centered on the risk associated with sea level rise (SLR) in the United States. Utilizing a comprehensive property-level dataset provided by Zillow, Bernstein et al. (2019) discovered that houses located in close proximity to the beach were sold at a significant 7% discount due to rising sea level concerns. Furthermore, they observed that properties near the sea, but not projected to be flooded within the next century, still endured a 4% selling discount. More recently, Nguyen et al. (2022) corroborated these findings of an SLR premium with data from the McDash dataset, suggesting that this premium was predominantly driven by long-term mortgages rather than short-term loans. Similarly, Painter (2020) identified the pricing of the SLR premium in U.S. long-term municipal bonds. Baldauf et al. (2020) investigated houses projected to be underwater and found that homes in areas where residents acknowledged climate change were sold at a lower price compared to those in areas where residents disputed climate change. Conversely, Murfin and Spiegel (2020) found no discernable price effects due to the risk of SLR. The authors maintained that their measure of relative sea level rise (RSLR), derived from changes in land elevation, could circumvent the inherent complications in housing amenities present in raw SLR data. This distinction, they argued, accounted for the discrepancies in results found in previous literature, despite differing data.

Most climate studies predominantly concentrate on larger firms primarily operating within the US market. Observations of actual default are scarce for these firms. By focusing on six European countries, Cathcart et al. (2020) reported that the bankruptcy rate for SMEs stands at 10.71%, compared to a mere 4.54% for larger firms. It is reasonable to anticipate a further decrease in the default rate when comparing large firms with public ones. This presents an obstacle to utilizing a firm's actual default history when examining the influence of climate change on default risk. As an alternative, prior research employs Merton's Distance to Default, derived from the stock prices of public firms, to assess default risk. Capasso et al. (2020) are among the first to probe the relationship between carbon emissions and credit risk, as measured by the distance to default. Investigating firms' scope 1 carbon emissions and carbon intensity, they concluded that firms with high carbon risk are more susceptible to default (i.e., lower distance to default). Moreover, they found that firms with substantial carbon footprints experienced a significantly lower distance to default post-Paris Agreement. In the same vein, Kabir et al. (2021) corroborated the negative implications of carbon emissions on the distance to default. In a recent study, Nguyen et al. (2023) also applied the Merton distance to default to gauge firm-level default risk, measuring climate risk using both carbon footprints and climate risk disclosures in annual filings. Unlike Capasso et al. (2020), they accounted for both scope 1 emissions (direct) and scope 2 emissions (indirect). Employing GMM estimation to address the pooled OLS exogeneity issue in Capasso et al. (2020), the authors found no evidence suggesting carbon footprints negatively impact a firm's default probability. In addition, they discovered the negative impact on default probability is confined to the disclosure of transition risk, not physical risk. However, they argued that physical risk disclosure in annual filings may not accurately reflect the actual physical risk faced by a firm. Hence, they recommended using an alternative measure of physical risk for future studies. Despite their findings, both studies encountered small sample sizes (less than 500 firms), limiting the generalizability of the results. Nguyen and Huynh (2023) affirmed the negative impact of firm-level climate change exposure on the distance to default, using a sample of 4,354 US firms. They derived their climate exposure data from Sautner et al. (2023), who employed a machine-learning algorithm to extract firm-level climate exposure from earnings conference calls. Aside from the standardized iterated Merton distance to default probability, Nguyen and Huynh (2023) also implemented the naive probability suggested by Bharath and Shumway (2008). They further noted that the negative effects were more pronounced for financially distressed firms and carbon-intensive industries. Employing both CDP surveys and natural disasters as climate risk measures, Huang et al. (2022) also found that climate risk increased a firm's likelihood of default (PD measured by Bharath and Shumway (2008)). Li et al. (2022) echoed these findings in China, concluding that firms with higher ESG scores generally exhibited lower default risk, as measured by the distance to default. While most studies use distance to default to assess default risk, some recent research has begun to utilize the Expected Default Frequency (EDF) from Moody's CreditEdge. Faralli and Ruggiero (2022) discovered that carbon emissions can adversely impact firms' default risk, as measured by Moody's EDF, through the asset volatility channel. They also echoed earlier findings that high-footprint firms were riskier after Paris Agreement.

Our initial contribution to the existing literature entails accurately assessing physical default events within the purview of climate risk studies. The Merton (1974) distance to default model conceptualizes a company's equity as a call option on the company's assets, with the company's debt serving as the strike price. This measure quantifies the extent to which a firm is unable to meet its financial obligations. For calculating the distance to default, the firm must initially be a publicly traded entity. Furthermore, the model makes several unrealistic assumptions, and while the measure is effective at ranking firms on a gradient from poor to good, it cannot accurately reproduce the true default probability. Contrarily, Moody's CreditEdge Expected Default Frequency (EDF) capitalizes on its distinctive, proprietary default data to derive physical probabilities of default. This process typically commences with computing the distance to default, subsequently mapping the derived distance to actual default data, thereby deriving a linear relationship between risk-neutral probabilities and tangible default probabilities. This methodology amends a significant flaw in the distance to default measure, particularly the discrepancy between the default probability computed using Merton's model and the actual default probability. Nevertheless, both measures are applicable only to public firms, despite the fact that SMEs constitute the majority of firms globally. Moreover, they cannot accurately depict a firm's true default history. We instead gather default data for small and micro-companies from Bureau van Dijk (BVD). BVD records any changes in a company's status and the corresponding date. We meticulously construct the status history of firms based on these status change notes, in line with the methodology of Cathcart et al. (2020). In default risk studies, it is critical to address survivorship bias. Compared to data obtained from the Amadeus/Orbis database online, our data, purchased in a single transaction, includes all historically insolvent companies. Conversely, the online version omits companies that have been inactive for a certain number of years (typically five, depending on whether Orbis or Amadeus is used). One might posit that annual data downloads could circumvent survivorship bias. However, our research indicates that Amadeus/Orbis may alter a company's identifier either systematically or randomly due to specific changes within the company. Merged data may pose problems as numerous firms with new identifiers could be pre-existing companies under different identifiers. Therefore, the advantage of purchasing the data in one transaction is evident for this study.

The current literature presents no uniform preference regarding the measurement of climate risk in studies examining its relationship with credit risk. Notably, chronic physical risk is often overlooked. The majority of studies, as mentioned earlier, focus on carbon emissions, ESG scores, natural disasters, and climate exposure inferred from earnings announcement data. However, no research has yet drawn a connection between chronic physical risk and default risk. As observed in the UNEP et al. (2018) report, existing climate change studies concentrate more on comprehending risks and opportunities linked to transition risk, with physical risks receiving less attention. The ECB (2021) economy-wide climate stress test suggests that, in the absence of policies fostering a transition towards a more sustainable economy, physical risk would impose a more considerable long-term impact compared to transition risk. The UNEP et al. (2018) report underlines the significance of assessing both incremental changes in climate conditions and extreme weather events when examining physical risks. Furthermore, carbon emissions, as a retrospective measure, primarily reflect past activities and may not accurately represent a firm's future climate risk. Moreover, consensus is lacking regarding the inclusion scope of carbon emissions in research. As for ESG scores, the calculation methods are often ambiguous and complex. Additionally, such scores are prone to exaggeration as part of "greenwashing" efforts, rendering them a noisy metric for assessing climate risk. Textual climate exposure at the firm level, as described by Sautner et al. (2023), can encapsulate stakeholder perspectives on a company's opportunities and the disruptions, both physical and regulatory, stemming from climate change. However, this measure is applicable only to public firms, and different algorithms or dictionaries could generate completely disparate firm-level risk measures. Previous studies predominantly aim to comprehend the impacts of extreme natural disasters on economies and corporate sectors, with less emphasis on incremental shifts in climate conditions, such as rising mean temperatures and changing precipitation patterns. As noted earlier in this paper, the increasing frequency and intensity of extreme weather events, including heatwaves and flash floods, result from changes in climate distribution. Therefore, it is vital to understand how these incremental climate changes can impact corporations, particularly the default probability of companies.

Our second contribution refocuses scholarly attention from large corporations to smaller enterprises, particularly small and micro firms, which are notably susceptible to physical risks. The health of the small business sector is integral to the stability of the Eurozone economy. In 2021, small and medium-sized enterprises (SMEs) constituted a staggering 99.8% of the non-financial business sector (NFBS) in the EU-27, employing around 83 million people, or 64% of total NFBS employment. Their economic significance is highlighted by their contribution of 52% of the NFBS's total value-added. Despite this, understanding of the climate risk impact on small businesses remains inadequate. No existing research has explored the correlation between incremental climate change and small business default risk. This paper addresses this gap, gauging physical climate risk using various temperature and precipitation measures. Our temperature and precipitation data, collected from the E-OBS dataset with a resolution of $0.1^{\circ}\times0.1^{\circ}$, are meticulously matched to the headquarters address of each firm in our dataset. The localized operations of small businesses justify our decision to proxy firm-level physical risk using temperature and precipitation data from their headquarters. We carefully match the weather data to the headquarters address of each firm in our data. In addition, the concentrated operation nature of the small business makes it valid to proxy firm-level physical risk using the temperature and precipitation from headquarters. This reduces the measurement error that inevitably arises in large firm studies (Addoum et al. (2020), Pankratz and Schiller (2021),Pankratz et al. (2023), Custodio et al. (2022)). Cathcart et al. (2022) was the inaugural study linking small business performance to higher temperatures. We expand climate risk research beyond performance to survival, demonstrating how small enterprise underperformance due to climate risk can ultimately result in bankruptcy. Concerning rising temperature risk, our findings suggest a $1°C$ increase in the yearly mean temperature can elevate a firm's default probability by 31 basis points. As for precipitation risk, a one standard deviation increase in the simple daily intensity index (mm/wet day) (SDII) can raise the default probability by 33 basis points. These results are both statistically and economically significant. Ou et al. (2018) observed that an increase in the average default rate from 0 to 9 basis points could trigger a substantial downgrade from Aaa to A, and a rise by 27 basis points could lead to a downgrade to Baa, which differentiates investment-grade from speculative-grade borrowers.

Our third key finding is the heightened susceptibility of firms with less substantial total assets, greater leverage ratios, and financial instability to both heat and precipitation risks. Prior research has demonstrated that larger firms possess operational flexibility that enables them to adjust to climate change implications; these adaptations range from business relocation and infrastructural enhancements to alterations in production methods and the broadening of insurance coverage (Berkhout et al. (2006); Hoffmann et al. (2009)). As summarized by Huang et al. (2022), earlier studies underscore the importance of sustaining organizational buffer resources, including backup facilities and financial reserves (for example, Linnenluecke et al. (2008); Vogus and Sutcliffe (2007); Hollnagel et al. (2006)). This capacity for adaptation may account for the null temperature impacts found by Addoum et al. (2020) on large US corporations. Significantly, this underscores the crucial need to investigate the small business sector concerning climate change, given their comparative lack of adaptability. It is reasonable to anticipate that negative effects will be more readily observable among smaller and less financially resourced firms. We ascertain that the yearly mean temperature measure predicts an additional increase of 16.4% in default probability for micro firms relative to small firms. Regarding the SDII index, we observe that the default probability for micro firms is likely to be 76.6% larger than that of small firms. In a similar vein, we find that both high-leverage firms and financially constrained firms demonstrate an increased probability of default in the face of escalating temperatures and intense rainfalls.

We have also discerned evidence of varying physical climate risk impacts on default probability across diverse geographical locations and industrial sectors. In the context of escalating temperatures, we do not identify a significant disparity between Southern European countries and the remaining nations in our sample. Conversely, we ascertain that Southern countries are more susceptible to the risk of intensified precipitation, which may precipitate a further escalation in default probability. Corroborating our earlier discoveries in the examination of firm performance (Cathcart et al. (2022)), we establish that energy and utility companies exhibit a reduced likelihood of default under chronic physical risk conditions. We additionally substantiate that the agriculture sector does not drive the negative effects of chronic physical risk on default probability. Intriguingly, in contrast to other industries, the agriculture industry manifests a decreased default likelihood in response to severe rainfall.

Huang et al. (2022) propose that managerial influence can significantly mitigate the detrimental climate impact on loan financing. They further argue in their paper that the widening spread of loan financing can be attributed to the upsurge in firms' implied default probability. We have noted that when the ultimate owner of a firm also operates in a managerial capacity—actively steering the company—the probability of default significantly reduces in the face of rising temperature and precipitation risks.

Lastly, our research correlates with studies examining the ramifications of climate change on the banking sectors. Curcio et al. (2023) scrutinized the association between billion-dollar climate disasters and the US banking and insurance sectors in a recent study, elucidating how certain extreme events can exacerbate risk to the overarching financial system. The ECB (2021) economy-wide climate stress test assesses the resilience of non-financial corporates (NFC) and euro-area banks to climate risks. One of the stress test's facets gauged the impact of physical and transition risks on NFC default probability, which in turn influences the banks' portfolio. The firm-level financial data for the ECB stress test was also collected from the Bureau van Dijk. Furthermore, the ECB sourced address-level physical risk scores from Four Twenty Seven. Instead of using actual default events to measure default probability, the ECB stress test employs Moody's Expected Default Frequency (EDF). A salient difference between our research and the ECB's stress test is the latter's omission of the physical risk measure in the default probability estimation model. Rather, they incorporated transition risk into various future scenarios: the orderly transition, disorderly transition, and the hot house world scenario. Subsequently, they projected the firm's accounting data and key macroeconomic indicators in each scenario. Prior to the projection stage, they conducted an estimation stage that generated a model for PD forecasting, obtaining observations on annual PDs from Moody's Credit Edge product. The projected firm accounting value and macro variables were further integrated into the estimated PD model to calculate the PD of firms under each scenario. Under the hot house world scenario, firms with high physical risk are projected to experience an approximate 25% increase in their default likelihood by 2050. This projection is five times greater than the anticipated increase for median and high-emission companies. The outcomes from ECB's stress test suggest that physical risk is considerably more conspicuous compared to transition risk in the long term, particularly in a scenario devoid of policies aimed at a greener economy.

The remainder of this paper is structured as follows: In Section 2, we detail the data and provide summary statistics. Section 3 outlines our methodology and explains the variable definitions. Our empirical baseline findings and a discussion on the robustness tests can be found in Section 4. Finally, Section 5 offers our conclusions and the potential impact of our research.

5.2 Data and Summary Stats

5.2.1 Sample and Variables

We sourced firm-level financial data and ownership data from Bureau van Dijk Orbis (BVD). This dataset includes all European companies—both large and SMEs, active and inactive—listed in the BVD database from 2005 to 2014, comprising approximately 20 million firm-year observations. Given our research interest, we filtered this data to focus on small and micro firms. In order to maintain a large number of observations, we adopted the total assets threshold from the definition of European small and medium-sized enterprises (SMEs) to identify micro and small firms in our sample. Consequently, firms with total assets between

2 million and 10 million were classified as small firms, whereas those with total assets below 2 million were deemed micro firms. We retained only those observations that included industry and accounting variable information (our control variables). Consistent with the methodology employed by Cathcart et al. (2020), we disregarded firm-year observations without available information on either the date of recording "status" or the "status" itself. Furthermore, we omitted data where the 'status' made the company's financial health ambiguous, specifically excluding categories like active branch, active dormant, active reorganization, and others with indeterminate conditions. In line with conventional corporate finance studies, we excluded financial and public sector firms. Subsequently, we removed countries with fewer than 5,000 annual firm observations, given the insufficiency of such a number for comprehensive country representation. Recognizing the variable recording practices of status changes across different countries, such as German firms typically not reporting the date of status change in Orbis, we meticulously calculated the percentage of active firm-year observations and disregarded countries with a value exceeding 99.99%—a suspiciously high value indicative of poor recording practices. Following these data cleansing steps, we concluded with approximately 5.2 million observations (0.85 million firms) spanning six European countries—United Kingdom, Italy, France, Spain, Portugal, and Belgium. Despite the absence of data from Germany, the included nations—UK, Italy, France, and Spain—are among the five largest economies in Europe, ensuring our

sample's representativeness of the EU economy.

For the temperature risk measures, we apply four different measures (three calculated from daily observations and one collected from annual indices):

- ***Mean temp***: The yearly mean temperature derived from the average value of *daily mean temperature* in a year.
- ***Anomaly***: The difference between the yearly mean temperature *Mean temp* and the rolling average of the yearly mean temperature *Mean temp* over the previous 30 years.
- ***Above 30*** : The total number of days above $30°C$ in a year.
- ***tx90p*** : Percentage of days with daily maximum temperature > 90th percentile of *daily maximum temperature.* To elaborate, we define TX_{ij} as the highest temperature recorded on day i during period j. Meanwhile, $TX_{in}90$ denotes the 90th percentile of *daily maximum temperature*, centered around a 5-day interval, for the baseline period of 1961-1990. The percentage of instances where $TX_{ij} > TX_{in}90$ during the baseline period (one year) is then calculated. For a more thorough explanation, please refer to the study conducted by Zhang et al. (2005).

Moving to the precipitation risk measures, we use four different ETCCDI indices:

- ***sdii***: The simple precipitation intensity index is calculated using the summation of *daily precipitation sum* on wet days divided by the number of wet days in a year. The wet days are defined as *daily precipitation sum* > 1mm.
- ***r1mm***: The total number of days when *daily precipitation sum* > 1mm in a year.
- ***r10mm***: The total number of days when *daily precipitation sum* > 10mm in a year.
- ***r20mm***: The total number of days when *daily precipitation sum* > 20mm in a year.

In the temperature risk regressions, we include an additional control for *Precipitation* which is the yearly average of *daily precipitation sum*. Furthermore, when the temperature risk is measured by the number of hot days *Above 30* and *tx90*, we also control for the corresponding cold day measures, *Below 0* the number of days below $0°C$ in a year, and *tn10p* the percentage of days with *daily minimum temperature* < 10th percentile of *daily minimum temperature*. Similarly, in the regression of precipitation risk, we additionally control for the *Mean temp*. All the above temperature and precipitation risk measures are defined at the location-year level.

Our temperature risk measures are comparable to those used in Addoum et al. (2020), Pankratz and Schiller (2021), Pankratz et al. (2023). Addoum et al. (2020)

gather weather data from the PRISM group, with a grid resolution of $4km \times 4km$. In contrast, our weather grid resolution is $0.1° \times 0.1°$, translating to $3.5km \times 11km$ at the latitude of $71.5°N$ and $10.3km \times 11km$ at the latitude of $25°N$ (refer to Appendix A.1 for further details). Pankratz and Schiller (2021) and Pankratz et al. (2023) amass global weather data from ERA5 at a coarser grid resolution of $0.3° \times 0.3°$, which is much coarser than the E-OBS data. We all employ $30°C$ as the absolute threshold for hot temperature. Studies by Seppanen et al. (2003) and Tanabe et al. (2013) indicate that productivity begins to decrease when the temperature reaches $25°C$, with this decline accelerating as the temperature surpasses $30°C$. In terms of the number of relative hot days measures, we adhere to the definition of ETCCDI indices. Addoum et al. (2020) initially calculate the number of days when daily maximum temperatures exceed the 90th percentile of daily maximum temperatures at the location-month level. They then sum up the monthly values to obtain the location-year count of relative hot days. Crucially, they do not utilize out-sample data to estimate the daily maximum temperature distribution as ETCCDI does. The relative measure calculation in Pankratz and Schiller (2021), Pankratz et al. (2023) mirrors ETCCDI. They construct the distribution of daily maximum temperature using a 10-day window around the day itself, spanning from 1980 to 1999.

Figure 5.1, same as Cathcart et al. (2022), illustrates the location-mean temperature trend, utilizing all E-OBS data from 1950 to 2020. A discernable upward trajectory in the yearly mean temperature across the European continent is evident, with the average mean temperature escalating by approximately 2.11°C from 1950 to 2020. This value surpasses the 1.5°C increase frequently reported in media, attributed to our data showcasing the land-only surface temperature. Principally, land, due to its lower heat capacity, is anticipated to heat more quickly than oceans when additional heat enters the climate system. The temperature anomaly from 2005 to 2016 across Europe is displayed in figure 5.2,. The predominance of red-colored subplots underscores a clear trend towards global warming.

In terms of firm-level control variables, we collect the ratio of net income to total assets (NITA), the ratio of current assets to total assets (CATA), and the number of years since a firm's inception (AGE) following the SME default risk study conducted by Cathcart et al. (2020). We exclude the SME dummy, concentrating solely on small and micro firms. For firm-level accounting variables, we perform winsorization at 1% and 99% thresholds within each country.

Several macroeconomic factors, varying at the country-year level, are included as robustness checks. Specifically, we acquire the natural logarithm of GDP growth (GDP) from the Eurostat Database, the yields on 3-month government bonds (GOVBOND) from the IMF-World Economic Outlook Database, and the log of sovereign credit default swap (CDS) spreads (SOVCDS) from Markit.

We convert the postcode of a firm's headquarters into longitudinal and latitudinal coordinates. Subsequently, we align the coordinates of weather grids with the firms' coordinates based on the nearest distance on the Earth's surface. This matching is highly precise, with the average distance between a firm's location and the corresponding weather grid being within 5km (for more details, refer to the Appendix in Chapter 4).

5.2.2 Summary statistics

Table 5.1the distribution of firms and their corresponding firm-year observations across various countries.This table also presents separate data for small and micro firms. A review of the table reveals that Italy contributes the highest number of firms and observations in the final data set, with 32.95% and 35.49% respectively. Combined, Italy, France, and Spain comprise 82.59% of the firms and 85.36% of the firm-year observations. The sample's geographical distribution ideally positions our data for examining physical risk. The ECB (2021) report asserts that companies exposed significantly to physical risk are predominantly located in Southern Europe. In this region, businesses with high physical risk constitute a proportion ranging from 25% to nearly 100% of all firms in the respective countries. Italy and Spain, in particular, represent a considerable fraction of the total exposure to physical risk among the European firms in the ECB study.

Furthermore, table 5.1 distinguishes between insolvent and bankrupt states, while regression analyses differentiate only between active and inactive states. Companies are considered active if their status in the Orbis database is labeled as ‘Active’. If the status in Orbis denotes ‘Active default of payment’, ‘Active rescue plan’, or ‘Active insolvency proceedings’, these companies are classified as insolvent. Lastly, companies are categorized as bankrupt if their status in Orbis signifies ’Bankruptcy’, ’In liquidation’, ‘Dissolved’, ‘Dissolved bankruptcy’, or ‘Dissolved liquidation’. The average bankruptcy rate of small and micro firms in our dataset stands at 10.62%, with Italian firms exhibiting the highest bankruptcy rate at 13.93%. Notably, the bankruptcy rate for small firms is typically higher than that for large corporations. As a point of comparison, Cathcart et al. (2020) report a 4.54% bankruptcy rate for large firms with total assets exceeding 43 million euros.

We observed deferential bankruptcy rates between small firms and micro firms, at 7.87% and 9.2%, respectively. Nonetheless, this difference is less marked than the discrepancy observed between SMEs and large corporations in Cathcart et al. (2020), where bankruptcy rates stood at 4.54% and 10.71% respectively. The bankruptcy rates for small firms (7.87%) and micro firms (9.36%) might appear incongruous as neither exceeds the average bankruptcy rate (10.62%). This is attributed to the methodology employed, where the bankruptcy rate is calculated by dividing the number of default firms by the total number of firms in each category, either small or micro. However, a firm’s total assets can fluctuate around the €2 million threshold, which subsequently modifies its classification. Notably, the total count of small (426,380) and micro firms (611,715) surpasses the total number of firms (854,865) documented in table 5.1.

Table 5.2 enumerates the number of insolvent and bankrupt firms for each sample year. As anticipated, the yearly default rates peaked following the global financial crisis and the European Sovereign debt crisis in 2009, 2012, and 2013. Post 2008, evidence consistently indicates that micro firms bear a higher default probability than small firms, with α exceeding 1.

To provide a comprehensive depiction of insolvency and bankruptcy among our small and micro firms, we incorporated firms with singular observations in the aforementioned table. However, for regression analyses with firm fixed effects, firms with only a single year's observation will be automatically omitted. The succeeding summary statistics are derived from firm-year observations used in the baseline regression model.

Table 5.3 outlines the industrial distribution based on the Orbis NACE categorization. Sixteen distinct sectors are represented, with Wholesale, Manufacturing, and Construction dominating, contributing 29.72%, 19.98%, and 16.11% of the overall sample respectively. Conversely, the Mining and Quarrying sector is least represented, contributing a mere 0.39% of the total, with only 20,192 observations. However, even this smallest industry offers a significant number of observations, enabling us to examine the variable impacts of climate risk across multiple sectors.

Table 5.4 provides a summary of the control variables employed in the regression. Micro firms account for 60.8% of the observations in the entire sample. On average, micro and small firms utilize 71% liabilities to finance their operations. The average age of firms in our sample stands at 16.8 years. However, this is marked by a high standard deviation, with the minimum age being less than one year and the maximum age exceeding 100 years. The median GDP growth rate is 0.652%, while the average 3-month government bond yield for the sample period is 1.75%.

Table 5.5 presents the summary statistics of temperature and precipitation measures. The mean annual temperature in our sample is 13.606 °C, with a standard deviation of 2.566 °C. Both temperature anomalies are positive, illustrating an evident global warming trend. For robustness, we apply an alternative method to compute the temperature anomalies. Rather than subtracting the 30-year rolling mean, we subtract the 30-year mean temperature from 1974 to 2003, a period that does not overlap with our estimation window. Given the ongoing nature of global warming, the latter measure is anticipated to yield a larger value. The relative percentage of hot and cold days is also noteworthy. The mean value for the relative hot days' measure, tx90p, is 20.835%, while the value for the cold days' measure, tn10p, is 6.969%. Both metrics capture the percentage of hot or cold days exceeding the 10th percentile tail value of the daily maximum or minimum temperature, theoretically expected to be 10%. This evidence suggests that the temperature measures distribution has shifted towards warmth. For precipitation measures, the summary statistics also demonstrate logical coherence. The number of intense precipitation days decreases as we adopt more stringent definitions, i.e., moving from r1mm to r20mm.

5.3 Methodology

We estimate the default probability employing a binary linear model integrated with high dimensional fixed effects. We opt for the binary OLS model over the logit model due to its capability to accommodate firm fixed effects. Angrist and Pischke (2009) justified the use of OLS estimates for the limited dependent variable (LDV) study in Section 3.4.2 of their renowned econometric book, 'Mostly Harmless Econometrics'. They further elucidate that once coefficients derived from the nonlinear model are transformed into marginal effects, these effects should align closely with the coefficients from OLS. Dell et al. (2014) advocated using pooled ordinary least squares (OLS) regression coupled with firm fixed effects and industry-year fixed effects to causally ascertain the impacts of weather variables.

Moreover, standard errors are consistently two-way clustered at both the firm level and the industry-year level. For the second cluster dimension, we integrate the interaction between year and industry to ensure adequate cluster groups in the year dimension, thereby circumventing the issue of small cluster bias (Abadie et al. (2022)). As posited by Addoum et al. (2020), two-way clustered results exhibit more robustness than standard errors clustered solely at the firm level or adjusted for spatial correlations.

$$DefaultState_{i,j,t} = \theta_i + \theta_{j,t} + \sum_{t=-2}^{-1} \rho T_{i,t} + \sum_{t=-2}^{-1} \gamma P_{i,t} + \epsilon_{i,j,t} \tag{5.1}$$

$$DefaultState_{i,j,t} = \theta_i + \theta_{j,t} + \sum_{t=-2}^{-1} \rho T_{i,t} + \sum_{t=-2}^{-1} \gamma P_{i,t} + \beta_1 X_{i,t-1} + \beta_2 X_{c,t-1} + \epsilon_{i,j,t} \tag{5.2}$$

Equation 5.1 serves as our reference model, where i,j,t indicates company, sector, and annual indices respectively. The *DefaultState* variable is a dummy indicating corporate insolvency status; it adopts a value of 0 for solvent firms and 1 for firms undergoing bankruptcy or insolvency. θ_i accounts for firm fixed effects, while $\theta_{j,t}$ caters to the industry-year fixed effect. Considering that a firm's head office weather conditions, encompassing temperature and precipitation, could correlate with its specific business strategies, industrial attributes, and annual trends, we incorporate these unique weather shocks for each firm and industry-year to accurately assess the impact of climate risk on default probability. Our key hypothesis assumes that weather variables are randomly distributed and exogenously determined, conditioned on spatial and temporal fixed effects, an approach thoroughly expounded in studies by Auffhammer et al. (2013) and Dell et al. (2014).

$T_{i,t}$ and $P_{i,t}$ represent our various temperature and precipitation exposures. Following the climate literature suggestion of Auffhammer et al. (2013), we incorporate precipitation when analyzing the effects of rising temperatures to control for the historical correlation between precipitation and temperature in the same location. Similarly, we consider temperature when assessing the risks associated with precipitation. It remains ambiguous ex-ante as to when the financial repercussions of heat and precipitation become apparent and eventually lead to corporate bankruptcy. Corporations often necessitate an extended period to navigate the bankruptcy procedure following a negative shock, especially when the shock constitutes an incremental (rather than acute) physical risk. For the control variables, we adhere to Cathcart et al. (2020) and incorporate a lag of one period. As for our primary variable of interest, the temperature and precipitation exposures, we include two lags in our main tests. Previous literature utilizing quarterly data posits that the impact of weather on firm performance can exhibit a lag of up to three quarters(Pankratz et al. (2023)). Furthermore, Barrot and Sauvagnat (2016) also identify lagged effects following environmental shocks.

In equation 5.1, in alignment with Addoum et al. (2020), Pankratz et al. (2023) and Pankratz and Schiller (2021), we abstain from including any firm or country time-varying control variables to address the so-called "over-controlling" or "bad controls" issue (Angrist and Pischke (2009)). Additionally, we evaluate equation 5.2 as a robustness check by including firm-year and country-year control variables listed in Cathcart et al. (2020). Our findings remain predominantly unaltered.

5.4 Results

5.4.1 Heat Exposure, Precipitation Exposure and Default Probability

Table 5.6 and table 5.7 present the estimated results for our heat and precipitation measures, respectively. As discernible from 5.6, only the heat measures lagged by two periods significantly affect a firm's default probability. Conversely, in table 5.7, both one-period and two-period lagged precipitation measures substantially augment the default probability of a firm. Consequently, we prioritize the analysis of precipitation risk by incorporating both these lags in subsequent sections. For the heat risk analysis, we transition from employing two lags to a single lag in the remainder of the study.

Table 5.8 exhibits the results for one-period lagged heat risk. Columns 1, 3, 5, and 7 display the regression outcomes of equation 5.1, whereas columns 2, 4, 6, and 8 present the results of equation 5.2. The outcomes from both model specifications remain consistent across all heat measures. In equation 5.2, we also account for the country-year linear trend by controlling country-level macroeconomic conditions. For the remainder of the paper, we will focus on interpreting the economic implications of regression results derived from equation 5.1 to circumvent potential over-controlling issues. We find $1°C$ increase in mean temperature raises the default probability by 33.7 basis points, and a one standard deviation increase in the mean temperature escalates the default probability by 86.5 basis points. Similar findings are affirmed when we employ temperature anomaly as a proxy for global warming rather than the level of mean temperature, with a $1°C$ increase in the temperature anomaly prompting a 32.6 basis points surge in default probability. Switching focus to the absolute number of hot days measures, we find a one standard deviation increase in the number of days above 30°C triggers a 13.7 basis points rise in the default probability. Given that adaptation to hot temperature thresholds may vary from location to location, we further investigate how the relative hot days measure influences a firm's financial distress. We observe a one standard deviation increase in the percentage of days above the 90th percentile heightening the default probability by 18.6 basis points. These positive impacts on probability are consistent with the findings of the ECB (2021) comprehensive climate stress test. The test posits that without interventions to mitigate climate risks, the financial ramifications for businesses from extreme weather conditions could amplify considerably, potentially detrimentally affecting their creditworthiness. Our results also corroborate previous findings suggesting heat exposure can adversely impact a firm's profitability, revenue, sales, and individual productivity(Cathcart et al. (2022), Addoum et al. (2023), Pankratz et al. (2023), Pankratz and Schiller (2021), Seppanen et al. (2003),Tanabe et al. (2013)).

Table 5.7 presents the findings related to precipitation risk. Consistent with the baseline results for heat risk, we observe a persistent positive effect of precipitation risk on a firm's default probability. Accordingly, our attention will be directed towards the interpretation of the results from columns 1, 3, 5, and 7. Notably, both one-period and two-period lagged precipitation measures significantly contribute to the increased probability of default. We will subsequently integrate the effects of these two lags to elaborate on the economic implications. With respect to the simple precipitation intensity index, a one standard deviation increase escalates the default probability by 32.4 basis points. For the number of intensive rainfall days, we discern more pronounced positive effects when adopting more rigorous precipitation measures. The additional day when daily rainfall exceeds 1mm, 10mm, and 20mm increases the default probability by 1.2, 2.5, and 5.3 basis points respectively.

However, relative to temperature studies, investigations concerning the impacts of intense precipitation on corporate performance are rather scarce. Among the limited evidence, based on data from Indian monsoons, Rao et al. (2022) reveal a significant reduction in market-based evaluations of rainfall-sensitive companies, especially following instances of severe deviations in rainfall patterns. Kumar and Parikh (2001) demonstrate that a 7 percent increase in rainfall corresponds to an approximate 8.4% decrease in overall net revenue at the farm level in India. Pankratz and Schiller (2021) found that an additional flooding day at the supplier's location diminishes customer profit by 7 basis points.

Our findings above are statistically and economically meaningful. Moody's statistics suggest that a 27 basis points rise in the probability of default can precipitate a downgrade from Aaa to Baa, converting a best investment-grade borrower into a speculative-grade one. Our observations regarding the impacts of heat and precipitation risks on default probability are also in alignment with findings on other climate exposures. These include studies such as Li et al. (2022), Carbon Emissions (Capasso et al. (2020), Nguyen et al. (2023), Kabir et al. (2021), Faralli and Ruggiero (2022)), climate disaster(Huang et al. (2022)), firm-level survey measures (Huang et al. (2022)), firm-level textual measures (Nguyen and Huynh (2023))on Merton's distance to default, and Moody's expected default frequency.

5.4.2 Micro firms and Financial Constraints

Relative to their larger counterparts, small firms typically possess fewer resources and limited expertise to manage climate risk. This situation is compounded by the information asymmetry between external investors and these smaller firms, which often impedes their ability to secure funding necessary for managing climate risks. Unlike large corporations, Small and Medium Enterprises (SMEs) are unable to redistribute resources among different factories and business segments when faced with extreme weather events, as highlighted by Custodio et al. (2022). Cathcart et al. (2020) discovered, in a study on the default risk of SMEs, that despite the non-current liability ratio, the interaction between the SME dummy and the leverage ratio always yields a significantly positive result. The impact of increased leverage on SMEs' default probability is 53% greater than that on large firms. This suggests that firm size is a considerable factor, leading us to expect varied weather impacts between small and micro firms.

Expanding upon this premise, we have modified our baseline model by introducing a firm-size dummy to identify micro firms when interacting with the weather variables. Table 5.9 presents the findings for heat risk exposures. Aside from the temperature anomaly, we consistently find that micro firms experience more severe impacts from heat exposures. Data indicating the mean temperature suggests that micro firms' default probability will rise by an additional 16.4% compared to small firms (0.052%/0.317%). Information relating to the relative number of hot days reveals that micro firms face an approximately doubled default probability compared to small firms. For the number of days above 30°C, we find that the baseline positive finding is predominantly observed among micro firms.

Table 5.10 reports the results for precipitation risk. For the simple precipitation intensity index, we observe an 86.5% ((0.039%+0.038%)/(0.053%+0.036%)) larger increase in the default probability for micro firms. Turning to the number of intensive rainy days, we discover that the differential impacts between small and micro firms become more apparent under a stricter definition. For the number of days when daily precipitation exceeds 20mm, we record an additional 52.4% increase in the default probability for micro firms.

Small firms, due to the prevalent issue of information asymmetry, are more prone to financial constraints. Size is a key determinant of financial constraint measures, as proposed by Hadlock and Pierce (2010). Given that micro firms experience more adverse impacts (higher default probability), we hypothesize that financially constrained firms would encounter similar challenges as micro firms when dealing with climate risk. We adopt the methodology of Schauer et al. (2019) to generate a dummy variable indicating a firm's financial constraint status. Unlike other financial constraint measures (SA index, KZ index) derived from large firms, Schauer et al. (2019) derived this measure from an extensive sample of private European firms, making it particularly apt for our dataset of European small and micro firms. This measure is a weighted average calculated from the firm size, return on assets, cash holdings, and interest coverage. A higher score suggests a higher degree of financial constraints for a firm. Based on Schauer et al. (2019), firms in the top 20% of the financial constraint score distribution are defined as financially constrained firms.

Table 5.11 reports the results for heat risk. Our findings mirror those from the study of micro firms. A $1°C$ rise in the mean temperature leads to a further 21.4% (0.053%/0.248%) increase in the default probability of financially constrained firms. The rise in default probability resulting from absolute hot days is predominantly driven by financially constrained firms. Regarding the relative heat measure, the impacts on financially constrained firms are 2.3 times greater than those on financially sound firms. Table 5.12 presents the outcomes for precipitation risk. We consistently observe that financially constrained firms are more negatively affected (higher default probability) by intensive precipitation. For the simple precipitation intensity index, we observe an additional 52.3% ($0.059\%/(0.076\% + 0.036\%)$) rise in the default probability for financially constrained firms. As we consider the number of intensive rainy days, we find that the coefficient for financially constrained firms is 1.4 times larger than that for financially healthy firms. Drawing on the Stern Review as an external shock to climate change awareness, Javadi et al. (2023) found that financially constrained firms tend to respond more significantly by augmenting their cash reserves compared to their unconstrained counterparts.

5.4.3 Industry effects

The Task Force on Climate-related Financial Disclosures (TCFD) defines "climate-related opportunity" as "the potential positive impacts related to climate change on an organization". A report by the UNEP et al. (2018) provides a framework to evaluate these opportunities for banks concerning physical climate risk. Although the report does not portray climate change as beneficial, it emphasizes understanding the heterogeneous impacts of climate change. The differential impact of weather across industries has been documented in several studies. For instance, Addoum et al. (2020) note that over 40% of industries are significantly affected by temperature shocks, experiencing both gains and losses due to climate risk. Studies by Pankratz and Schiller (2021), Custodio et al. (2022), and Graff Zivin and Neidell (2014) find heat-sensitive industry firms are more negatively impacted by heat exposure. In this section, we concentrate on two particular sectors: the energy and utility sector, and the agriculture sector, both of which need to be separately studied according to previous economic climate literature.

We consolidate the energy and utility sectors into a dummy variable and interact it with heat and precipitation measures. Table 5.13 and table 5.14 present the results for heat risk and precipitation risk, respectively. We find consistent evidence suggesting the energy-utility sector is less impacted by heat risk. The increase in default probability decreases by 72% (0.245%/0.340%) for the mean temperature increase and 76% (0.251%/0.330%) for the temperature anomaly increase. For the number of hot days' effects, we observe that the negative impacts on default probability are nullified for the energy-utility sector. Regarding precipitation risk, there is weak evidence that the energy-utility sector is less affected by the number of intensive rainy days, with a 52% and 35.2% less increase in default probability for r10mm and r20mm, respectively.

We also interact the agriculture industry dummy with the weather variables in the baseline model, with the results for heat risk and precipitation risk reported in table 5.15 and table 5.16, respectively. As for the heat risk, we find agriculture firms are less affected by the rising temperature. We find that agricultural firms are less affected by rising temperatures, an observation that aligns with Kim (2012) assertion that increased temperatures and elevated CO2 levels could enhance agricultural output due to extended growing seasons and the fertilizing effect of CO2. Furthermore, warmer conditions could mitigate cold weather's adverse effects on winter crops. With regard to precipitation risk, we find that the default probability for the agriculture industry decreases by 51.2% $(0.070\%/(0.076\% + 0.059\%))$ compared to other industries when confronted with intensive precipitation.

5.4.4 Manager-Owner

Our exploration continues on how weather conditions can affect a company's performance, focusing particularly on the "agency problem" between firm owners and management. When owners also serve as managers, they are more exposed to firm-specific risks, given their investment in personal wealth and professional skills within the company. This scenario, as Brisley et al. (2021) posit, could potentially diminish their risk tolerance, fostering a need to mitigate climate-related risks. Moreover, Huang et al. (2022) illustrate that diverse managerial strategies can significantly alleviate a company's financial challenges when addressing climate change. Consequently, we hypothesize that firms whose ultimate owner actively participates in day-to-day management can lower the probability of default compared to firms managed by a professional manager. Utilizing the ownership data from Orbis, we define a subsample where all firms are controlled by a Global Ultimate Owner (GUO). Our threshold to define a GUO selection path is 50.01%, suggesting that the GUO has full control of the firm (for more details, see Kalemli-Ozcan et al. (2015)). More importantly, we can determine whether each GUO serves as a manager.

We establish a GUO-Manager dummy to recognize the managerial role of the GUO in the company, and interact it with our weather variables in the baseline model. Table 5.17 and Table 5.18 report our results for heat risk and precipitation risk, respectively. For the temperature anomaly measure, we observe an increase in the default probability of firms run by a GUO manager. However, this increase is 67.3% smaller than that in firms managed by a professional manager. For the remaining heat and precipitation measures, we note the previously observed increase in default probability is absent in firms with a GUO manager.

5.4.5 Climate risk, Firm Profit, and Default Probability

In the thesis, the findings of Chapter 4 and Chapter 5 collectively reveal a pivotal linkage between climate risk, reduced profitability, and increased default risk among small and micro European enterprises (SMiEs), especially in financially constrained firms. Chapter 4 highlights how climate change, manifesting in higher temperatures, leads to a marked reduction in profitability across various industries. This universal decline in profitability, regardless of the sector, serves as a critical conduit through which climate risk escalates into heightened default risk, as demonstrated in Chapter 5.

Particularly for financially constrained SMiEs, this connection becomes more pronounced. These firms typically have limited access to additional capital, making them heavily reliant on their operating income for both survival and growth. When climate change erodes this profitability, these enterprises lack the financial buffer to absorb the shock, pushing them closer to the brink of default. Their constrained financial situation leaves little room for investing in adaptive measures to mitigate climate impacts, contrasting with larger or less financially restricted firms that might have more resources or options to pivot and adapt.

Thus, for financially constrained SMiEs, the pathway from climate-induced profitability losses to increased default risk is not just a theoretical concept but a practical reality. The universality of this pathway across industries underscores the pervasive nature of climate risk and highlights the crucial need for strategies focusing on financial resilience and adaptive capacity, particularly for financially vulnerable SMiEs.

5.5 Other Robustness

We conducted a series of tests to verify the robustness of our findings. In the primary analysis, we determined the count of relative hot days adhering to the ETCCDI definition. Additionally, for robustness check, we employed the definitions of relative hot days as proposed by Addoum et al. (2020), and Cathcart et al. (2022). To calculate this measure, we analyzed the distribution of the highest daily temperature for each specific month/location, utilizing historical data spanning from 1974 to 2003. Subsequently, we counted the number of days in each month/location during our sampling period (2004–2014) that exceeded the 90th percentile of that month's maximum temperature distribution. Ultimately, we aggregated all the days exceeding the 90th percentile across all months in the considered year for each firm's location.

Rather than defining temperature anomaly as the difference between the current year's mean temperature and the rolling mean temperature of the previous 30 years, we computed the temperature anomaly by subtracting the average yearly mean temperature from 1974 to 2003, a time frame that doesn't overlap with our estimation period. Unreported results substantiated our primary findings for these two alternative heat measures.

While the financial constraint measure developed by Schauer et al. (2019) is suitable for our study involving European small and micro firms, we forfeited approximately 2 million observations to compute the financial constraint score.

To preserve these observations and circumvent biased measures specific to large firms, we identified firms with higher leverage ratios as financially distressed. As posited by Hennessy (2004), a firm under a substantial debt burden eventually succumbs to a debt overhang situation, rendering it incapable of securing additional funding to mitigate climate risk. We ranked firms according to their leverage ratio, categorizing the top 20% as high-leverage firms. Then, we incorporated the high-leverage dummy into our baseline model, interacting it with the weather variables. Appendix table 5.A.1 and 5.A.2 detail our results, indicating that similar to financially constrained firms, high-leverage firms also suffer more negative impacts (evidenced by a positive interaction term) from both heat and precipitation risks.

Rather than limiting our focus to a sub-sample with GUO information, we utilized the complete dataset and segmented the sample into three groups: firms without a GUO, firms with a GUO where the GUO is not a manager (identified by a GUO dummy), and firms with a GUO where the GUO is concurrently a manager (identified by a GUO-Manager dummy). Subsequently, we interacted the GUO and GUO-Manager dummies with the weather variables to perform the regressions. The outcomes, detailed in Appendix table 5.A.3 and table 5.A.4, align with the findings presented in section 4.4. We observed a negative interaction term for both the GUO dummy and GUO-Manager dummy, with the interaction coefficients of the GUO-Manager dummy being more negative.

Lastly, we investigated the possibility of adaptation among southern European countries. Particularly concerning heat risk, citizens from Southern Europe may acclimatize to hot weather more easily compared to their counterparts from the rest of Europe. Based on this hypothesis, we classified Spain, Italy, and Portugal as Southern countries. The results are presented in 5.A.5 and Table 5.A.6. Pertaining to heat risk, evidence of adaptation was only observed in the regression for the number of relatively hot days when control variables were included. Regarding precipitation risk, Southern countries appear more negatively affected, indicated by a positive interaction term in most instances

5.6 Lessons from climate Risk

The research's exploration of climate risks for small and micro European firms (SMiEs) inadvertently reveals potential positive aspects, particularly in the realms of innovation and firm creation. While climate change undoubtedly presents challenges, it also acts as a catalyst for adaptation and innovation. Faced with increasing temperatures and precipitation risks, SMiEs are compelled to seek novel solutions, potentially leading to the development of new products, services, and business models that are resilient to climate change.

In agriculture, for example, intensified rainfall might benefit rainfed agriculture, encouraging the sector to innovate in water management and crop selection. Energy companies, showing resilience to higher temperatures, might innovate in renewable energy technologies or efficient cooling systems. This necessity-driven innovation could lead to the emergence of new market niches and business opportunities, fostering economic dynamism and diversification.

Moreover, the heightened risk of default under climate change pressures could prompt SMiEs to rethink their operational and financial strategies, leading to more robust and sustainable business practices. This shift might also spur the creation of new firms specializing in climate adaptation solutions, offering services ranging from climate risk assessment to the implementation of adaptive technologies.

In summary, while the adverse effects of climate change pose significant risks to SMiEs, they also provide a unique impetus for innovation, adaptation, and the birth of new business ventures, ultimately contributing to a more resilient and diverse economic landscape.

5.7 Conclusion

Utilizing default data from six European countries, we analyze the impact of escalating physical risk on the default probability of small and micro European firms. Specifically, we explore the effects of increasing temperature and intensive precipitation risk, which may result in more frequent and severe heatwaves and flash floods. Our empirical findings suggest that the underperformance in small business sectors, attributable to climate risk, may ultimately culminate in the firm's bankruptcy. A one standard deviation surge in mean temperature and the simple intensity index could raise a firm's default probability by 86.5 and 32.4 basis points, respectively. Such increases in probability could demote an Aaa-rated borrower to a Baa-rated borrower. Furthermore, one standard deviation of mean temperature in our sample equates to 2.56°C. In contrast, the ECB (2021) report forecasts at least a 3°C rise above pre-industrial levels by 2100 under the hot house world scenario. This implies that substantial increases in default probability are highly plausible if no regulatory measures or policies are implemented to curb climate change.

We also explore various channels through which physical risk impacts firms' default probability heterogeneously. Our findings suggest that firms with limited financial resources and smaller total assets are more prone to default. In comparison to small and financially unconstrained firms, we record a further surge in the default probability for micro and financially constrained firms.

We underscore the necessity of understanding the diverse impacts of climate risk on different industries. Specifically, our findings indicate that the energy and utility sectors are less affected. Lastly, we discover that when the ultimate owner also serves as the firm's manager, they can potentially mitigate the negative effects of rising temperature and intensive precipitation.

For small and micro European enterprises (SMiEs), this research has crucial implications regarding their financial resilience in the face of climate change. It highlights an urgent need for these firms to integrate climate risk assessment into their business and financial planning. The findings that rising temperatures and increased precipitation significantly elevate default probabilities indicate that SMiEs must develop robust adaptation strategies. This might involve diversifying business locations to mitigate geographical climate risks, investing in technology and infrastructure that can withstand extreme weather, and strengthening financial buffers.

Furthermore, the heightened vulnerability of firms with smaller assets and higher leverage ratios suggests that careful financial management and seeking stable funding sources are essential. SMiEs should consider climate risk as a critical factor in their operational and strategic decision-making. For industries and regions with specific susceptibilities, tailored adaptation plans are necessary. Overall, this research underscores the importance of proactive climate resilience planning for SMiEs, essential for their long-term sustainability and economic contribution.

5.8 Figures and Tables

Figure 5.1: Mean temperature in Europe from 1950 to 2014

This figure illustrates the mean temperatures in Europe from 1950 to 2014, based on near-surface data from E-OBS. The "mean temperature" is the average daily mean temperature of all areas covered in E-OBS in a year.

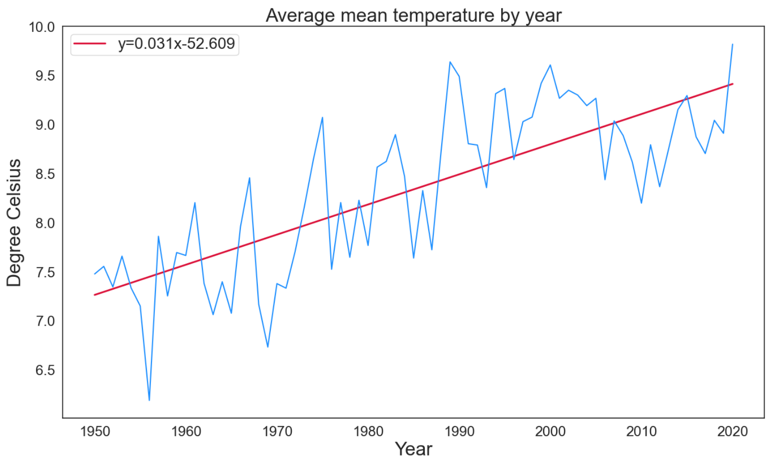


Figure 5.2: Temperature anomaly in Europe by year, 2003–2014

This figure depicts the mean-temperature anomalies across the European continent from 2003 to 2014. A "temperature anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location.

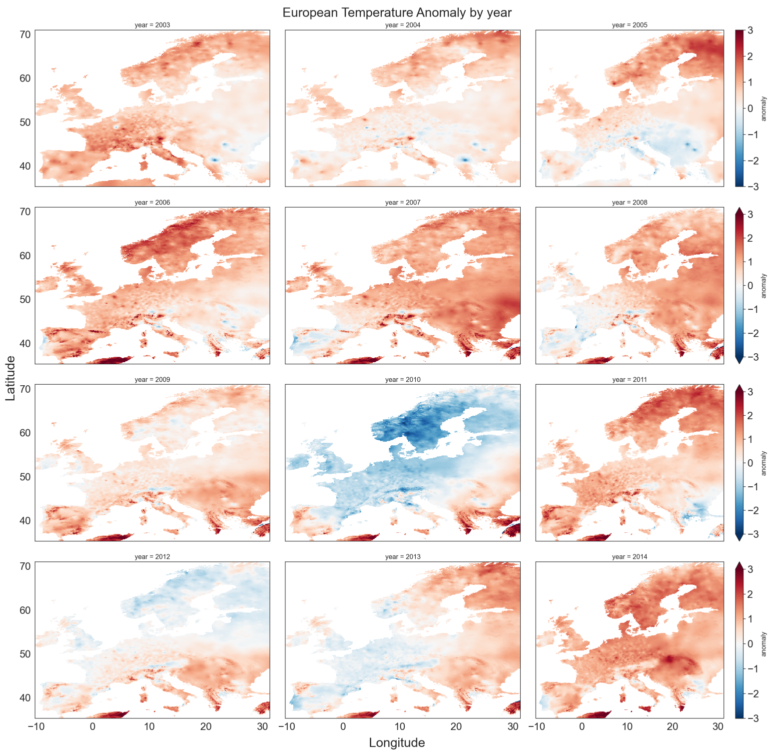


Table 5.1: Active, insolvent, and bankruptcy firms by country

This table describes the distribution of our sample across the European countries in our sample. Firm-year observations are classified into three alternative states: Active, Insolvent, and Bankrupt. Firms are Active if their Orbis "status" is Active; Insolvent if their Orbis "status" is either Active default of payment, Active rescue plan, or Active insolvency proceedings; and Bankrupt if their Orbis "status" is either Bankruptcy, In liquidation, Dissolved, Dissolved bankruptcy, or Dissolved liquidation. The last six columns present the number of firm-year observations (and percentages) for each state. The sample period ranges from 2005 to 2014.
$a = \frac{Firms\,in\,Country}{Total\,Firms}$;$b = \frac{Observations\,in\,Country}{Total\,Observations}$;$c = \frac{Active\,Firms\,in\,Country}{Firms\,in\,Country}$;$d = \frac{Insolvent\,Firms\,in\,Country}{Firms\,in\,Country}$;
$e = \frac{Bankrupt\,Firms\,in\,Country}{Firms\,in\,Country}$.

	Frims		Firm-year obs		Active state		Insolvent state		Bankrupt state	
	N.	a(%)	N.	b(%)	N.	c(%)	N.	d(%)	N.	e(%)
					Overall sample					
Belgium	50,244	5.88	368,634	6.82	49,490	98.50	426	0.85	4,759	9.47
Spain	176,365	20.63	989,965	18.33	173,036	98.11	5,427	3.08	14,649	8.31
France	248,018	29.01	1,703,984	31.54	244,147	98.44	8,808	3.55	24,706	9.96
United Kingdom	56,921	6.66	213,770	3.96	54,305	95.40	870	1.53	5,948	10.45
Italy	281,686	32.95	1,917,049	35.49	278,350	98.82	1,921	0.68	39,236	13.93
Portugal	41,631	4.87	208,707	3.86	40,735	97.85	3,317	7.97	1,520	3.65
Total	854,865	100	5,402,109	100	840,063	98.27	20,769	2.43	90,818	10.62
					Small Firms					
Belgium	33,248	3.89	182,263	3.37	32,749	98.50	218	0.66	1,999	6.01
Spain	93,829	10.98	435,316	8.06	91,446	97.46	3,047	3.25	7,257	7.73
France	88,452	10.35	453,833	8.40	87,065	98.43	2,342	2.65	4,713	5.33
United Kingdom	42,189	4.94	153,577	2.84	40,793	96.69	641	1.52	3,065	7.26
Italy	150,574	17.61	819,264	15.17	147,295	97.82	1,495	0.99	16,112	10.70
Portugal	18,088	2.12	82,522	1.53	17,689	97.79	1,541	8.52	406	2.24
Total	426,380	100	2,126,775	100	417,037	97.81	9,284	2.18	33,552	7.87
					Micro Firms					
Belgium	32,861	3.84	186,371	3.45	32,254	98.15	232	0.71	2,760	8.40
Spain	118,635	13.88	554,649	10.27	116,183	97.93	2,602	2.19	7,392	6.23
France	202,260	23.66	1,250,151	23.14	198,404	98.09	6,807	3.37	19,993	9.88
United Kingdom	21,460	2.51	60,193	1.11	19,912	92.79	236	1.10	2,883	13.43
Italy	206,370	24.14	1,097,785	20.32	203,001	98.37	524	0.25	23,124	11.21
Portugal	30,129	3.52	126,185	2.34	29,373	97.49	1,801	5.98	1,114	3.70
Total	611,715	100	3,275,334	100	599,127	97.94	12,202	1.99	57,266	9.36

Table 5.2: Number of defaults

This table reports the number (and percentage) of insolvent and bankrupt firms for each year of the sample. The percentages (in parentheses) are computed for the total number of firms in each year. Sample firms are then split into two subsamples: Micro and small corporations. If the value of a firm's total assets is no greater than €2 million, the firm is classified as a micro corporation; if the value of a firm's total assets is between €2 million and €10 million, it is classified as a small corporation. The table displays the number (and percentage for each subsample) of insolvent and bankrupt firms that are micro and small corporations. The last column is the ratio of the percentage of defaulted micro corporations to the percentage of defaulted small corporations.
$\alpha = \frac{\%MicroCoporation}{\%SmallCoporation}$.

Years	Overall sample		Micro Firms		Small Firms		α
	N.	(%)	N.	(%)	N.	(%)	
2006	6,108	1.35	3,566	1.26	2,542	1.50	0.839
2007	6,922	1.39	4,036	1.32	2,886	1.50	0.879
2008	10,204	1.93	6,099	1.89	4,105	2.00	0.947
2009	13,311	2.45	8,531	2.60	4,780	2.22	1.172
2010	11,861	2.15	7,249	2.17	4,612	2.12	1.019
2011	12,629	2.24	7,954	2.33	4,675	2.10	1.113
2012	14,670	2.57	9,347	2.70	5,323	2.35	1.149
2013	14,809	2.58	9,345	2.68	5,464	2.43	1.100
2014	12,158	2.16	7,534	2.21	4,624	2.07	1.067
2015	6,737	1.40	4,174	1.47	2,563	1.30	1.129
Total	109,409	12.93	67,835	11.21	41,574	9.88	1.135

Table 5.3: Industry distribution

This table shows the industry distribution of firm years in our sample. The industry classifications are according to the NACE Rev. 2 main section in Orbis. The sample period is 2005–2014.

NACE Rev. 2 main section	N.	Percent
Agriculture, forestry and fishing	112,915	2.15
Mining and quarrying	20,192	0.39
Manufacturing	1,047,938	19.98
Electricity, gas, steam and air conditioning supply	36,043	0.69
Water supply; sewerage, waste management and remediation activities	40,937	0.78
Construction	844,990	16.11
Wholesale and retail trade; repair of motor vehicles and motorcycles	1,558,638	
Transportation and storage	276,818	5.28
Accommodation and food service activities	234,797	4.48
Information and communication	163,720	3.12
Professional, scientific and technical activities	360,470	6.87
Administrative and support service activities	246,770	4.71
Education	47,306	0.9
Human health and social work activities	143,842	2.74
Arts, entertainment and recreation	60,519	1.15
Other service activities	48,525	0.93
Total	5,244,420	100

Table 5.4: Summary statistics of control variables

This table presents the summary statistics for control variables used in our regression analysis. The first three are country-specific variables: GDP is the 1-year GDP growth rate; GOVBOND is the 3-month government bond interest rate; SOVCDS is the logarithm of the government CDS spread; Micro is a dummy to identify micro firms, the value equals to 1 if the total asset of a firm is less than €2 million; LEVERAGE is the ratio of total liabilities to total assets; NITA is the ratio of net income to total assets; CATA is the ratio of current assets to total assets; AGE is the number of days since incorporation divided by 365. The sample period is 2005–2014.

Variable	Mean	Median	SD	Min	Max
GDP(%)	0.290	0.652	2.480	-7.076	4.223
GOVBOND(%)	1.751	1.244	1.559	-0.073	6.750
SOVCDS(%)	-0.767	-0.359	1.648	-4.375	2.443
Micro	0.608	1.000	0.488	0.000	1.000
Leverage	0.711	0.739	0.301	0.002	4.470
NITA	0.028	0.018	0.108	-0.973	0.631
CATA	0.697	0.784	0.274	0.001	1.000
AGE	16.773	13.912	13.005	0.427	104.849

Table 5.5: Summary statistics of weather variables

This table provides the summary statistics for the weather variables used in our regression analysis. "Mean temperature" is the average daily mean temperature over the year. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Anomal1" is the difference between the mean temperature and the average mean temperature between 1974 and 2003 in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Days below 0" is the total number of days in a year that saw temperatures below 0°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. "Tn10p" is the percentage of days with daily minimum temperature < 10th percentile of daily minimum temperature centered around a 5-day interval for the baseline period of 1961-1990. "precipitation" is the average daily precipitation sum in mm in a year. "Sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. The sample period is 2005–2014.

Variable	Mean	Median	SD	Min	Max
Mean temp	13.606	13.551	2.566	-2.138	20.991
Anomaly	0.370	0.392	1.000	-4.492	4.987
Anomaly1	0.823	0.850	0.692	-4.243	5.701
Days above 30	31.878	25.000	27.332	0.000	145.000
Days below 0	34.518	32.000	28.888	0.000	254.000
Tx90p	20.835	19.452	7.755	0.548	79.178
Tn10p	6.969	6.301	4.527	0.000	46.575
Precipitation	2.034	1.952	0.790	0.258	8.690
Sdii	8.209	8.084	2.455	3.730	23.918
R1mm	92.826	96.000	31.346	18.000	249.000
R10mm	23.325	21.000	11.597	1.000	111.000
R20mm	6.784	6.000	5.460	0.000	51.000

Table 5.6: A-The impact of temperature on firm default probability

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2). The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Mean temperature" is the average daily mean temperature over the year. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp (y-1)	0.049	0.029						
	[0.847]	[0.486]						
Mean temp (y-2)	0.281***	0.239***						
	[5.678]	[4.657]						
Anomaly (y-1)			0.031	0.011				
			[0.525]	[0.176]				
Anomaly (y-2)			0.274***	0.232***				
			[5.385]	[4.447]				
Days above 30 (y-1)					-0.003	-0.004*		
					[-1.301]	[-1.677]		
Days above 30 (y-2)					0.005**	0.005**		
					[2.228]	[2.567]		
Tx90p (y-1)							-0.008	-0.009
							[-1.351]	[-1.485]
Tx90p (y-2)							0.021***	0.021***
							[5.432]	[5.601]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,242,980	5,242,980
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.7: The impact of precipitation on firm default probability

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2). The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Sdii (y-1)	0.075***	0.078***						
	[6.271]	[6.803]						
Sdii (y-2)	0.057***	0.057***						
	[4.930]	[5.182]						
R1mm (y-1)			0.005***	0.006***				
			[3.308]	[4.293]				
R1mm (y-2)			0.007***	0.006***				
			[4.328]	[3.178]				
R10mm (y-1)					0.012***	0.015***		
					[4.718]	[6.002]		
R10mm (y-2)					0.013***	0.012***		
					[4.235]	[3.604]		
R20mm (y-1)							0.030***	0.034***
							[7.270]	[7.862]
R20mm (y-2)							0.023***	0.021***
							[4.586]	[4.251]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.8: B-The impact of temperature on firm default probability

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with lagged one-period heat exposures. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Mean temperature" is the average daily mean temperature over the year. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.337***	0.306***						
	[7.545]	[6.803]						
Anomaly			0.326***	0.296***				
			[7.067]	[6.428]				
Days above 30					0.005**	0.006***		
					[2.405]	[2.874]		
Tx90p							0.024***	0.025***
							[6.627]	[7.209]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.9: The impact of temperature on the default probability of micro firms

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with the micro-firm dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. “Micro” equals 1 if the firm is a micro firm in a given year. “Mean temperature” is the average daily mean temperature over the year. “Anomaly” is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. “Days above 30” is the total number of days in a year that saw temperatures above 30°C. “Tx90p” is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.317***	0.287***						
	[6.921]	[6.180]						
Mean temp x Micro	0.052***	0.047***						
	[5.226]	[5.304]						
Anomaly			0.316***	0.293***				
			[5.555]	[5.249]				
Anomaly x Micro			0.029	0.011				
			[0.674]	[0.280]				
Days above 30					0.003	0.003		
					[1.122]	[1.278]		
Days above 30 x Micro					0.005***	0.005***		
					[2.967]	[3.477]		
Tx90p							0.016***	0.017***
							[3.595]	[4.266]
Tx90p x Micro							0.016***	0.014***
							[4.391]	[3.983]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.10: The impact of precipitation on the default probability of micro firms

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the micro-firm dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. Micro" equals 1 if the firm is a micro firm in a given year. "Sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Sdii (y-1)	0.053***	0.058***						
	[4.289]	[4.804]						
Sdii (y-2)	0.036***	0.036***						
	[2.871]	[2.960]						
Sdii (y-1) x Micro	0.039***	0.035***						
	[3.150]	[2.861]						
Sdii (y-2) x Micro	0.038***	0.037***						
	[3.004]	[3.006]						
R1mm (y-1)			0.004**	0.006***				
			[2.463]	[3.452]				
R1mm (y-2)			0.005***	0.005**				
			[3.075]	[2.420]				
R1mm (y-1) x Micro			0.001	0.001				
			[0.768]	[0.401]				
R1mm (y-2) x Micro			0.003*	0.002				
			[1.802]	[1.052]				
R10mm (y-1)					0.010***	0.013***		
					[3.266]	[4.317]		
R10mm (y-2)					0.007**	0.007**		
					[2.579]	[2.025]		
R10mm (y-1) x Micro					0.004	0.004		
					[1.319]	[1.202]		
R10mm (y-2) x Micro					0.010***	0.009***		
					[3.116]	[2.857]		
R20mm (y-1)							0.026***	0.029***
							[4.976]	[5.373]
R20mm (y-2)							0.016***	0.014**
							[2.966]	[2.468]
R20mm (y-1) x Micro							0.009*	0.009*
							[1.658]	[1.762]
R20mm (y-2) x Micro							0.013**	0.013**
							[2.375]	[2.207]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.11: Firm default probability, temperature, and financial constraints

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with the dummy (Constraint) that highlights financially constrained firms. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Constraint" equals 1 when it is in the top 20% for its Schauer et al. (2019) score. "Mean temperature" is the average daily mean temperature over the year. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.248***	0.188***						
	[4.763]	[3.646]						
Mean temp x Constraint	0.053***	0.011						
	[3.874]	[0.956]						
Anomaly			0.252***	0.199***				
			[3.256]	[2.736]				
Anomaly x Constraint			-0.015	-0.104				
			[-0.075]	[-0.591]				
Days above 30					0.003	0.004*		
					[1.144]	[1.866]		
Days above 30 x Constraint					0.007***	0.004**		
					[4.093]	[2.100]		
Tx90p							0.011**	0.014***
							[2.056]	[2.915]
Tx90p x Constraint							0.025**	0.011
							[2.452]	[1.267]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318
R-squared	0.291	0.313	0.290	0.313	0.291	0.313	0.291	0.313

Table 5.12: Firm default probability, precipitation, and financial constraints

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the dummy (Constraint) that highlights financially constrained firms. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Constraint" equals 1 when it is in the top 20% for its Schauer et al. (2019) score. "Sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Sdii (y-1)	0.076***	0.082***						
	[6.660]	[7.850]						
Sdii (y-2)	0.036**	0.037**						
	[2.479]	[2.518]						
Sdii (y-1) x Constraint	-0.013	-0.016						
	[-0.427]	[-0.533]						
Sdii (y-2) x Constraint	0.059**	0.061**						
	[2.501]	[2.369]						
R1mm (y-1)			0.004**	0.006***				
			[2.243]	[3.011]				
R1mm (y-2)			0.006***	0.004				
			[2.920]	[1.380]				
R1mm (y-1) x Constraint			0.007	0.001				
			[1.514]	[0.298]				
R1mm (y-2) x Constraint			0.005	0.004				
			[1.054]	[0.892]				
R10mm (y-1)					0.011***	0.015***		
					[3.841]	[4.945]		
R10mm (y-2)					0.008*	0.004		
					[1.932]	[1.022]		
R10mm (y-1) x Constraint					0.010	0.004		
					[1.253]	[0.506]		
R10mm (y-2) x Constraint					0.020**	0.021**		
					[2.409]	[2.509]		
R20mm (y-1)							0.027***	0.033***
							[5.616]	[6.035]
R20mm (y-2)							0.013**	0.009
							[1.990]	[1.230]
R20mm (y-1) x Constraint							0.022*	0.018
							[1.710]	[1.297]
R20mm (y-2) x Constraint							0.034***	0.037***
							[2.773]	[2.838]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318	3,229,318
R-squared	0.291	0.313	0.291	0.313	0.291	0.313	0.291	0.313

Table 5.13: Impact of temperature on the default probability of Energy and Utility Sectors

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with the temperature variables interacted with the energy-utility dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. The energy-utility dummy is equal to 1 if the firm is operating in either the energy or the utility sector. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.340***	0.309***						
	[7.520]	[6.784]						
Mean temp x Energy Utility	-0.245**	-0.211**						
	[-2.361]	[-2.086]						
Anomaly			0.330***	0.299***				
			[7.047]	[6.408]				
Anomaly x Energy Utility			-0.251**	-0.210**				
			[-2.441]	[-2.064]				
Days above 30					0.005**	0.006***		
					[2.424]	[2.880]		
Days above 30 x Energy Utility					-0.008*	-0.006		
					[-1.667]	[-1.387]		
Tx90p							0.025***	0.025***
							[6.665]	[7.229]
Tx90p x Energy Utility							-0.029**	-0.025*
							[-2.286]	[-1.917]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.14: Impact of precipitation on the default probability of Energy and Utility Sectors

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the energy-utility dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. The energy-utility dummy is equal to 1 if the firm is operating in either the energy or the utility sector. "Sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Sdii (y-1)	0.075***	0.078***						
	[6.176]	[6.715]						
Sdii (y-2)	0.057***	0.056***						
	[4.848]	[5.093]						
Sdii (y-1) x Energy Utility	0.010	0.001						
	[0.323]	[0.032]						
sdii (y-2) x Energy Utility	0.017	0.016						
	[0.471]	[0.441]						
R1mm (y-1)			0.005***	0.006***				
			[3.300]	[4.268]				
R1mm (y-2)			0.007***	0.006***				
			[4.255]	[3.128]				
R1mm (y-1) x Energy Utility			-0.005	-0.004				
			[-1.348]	[-1.102]				
R1mm (y-2) x Energy Utility			0.002	0.002				
			[0.438]	[0.465]				
R10mm (y-1)					0.012***	0.015***		
					[4.726]	[6.005]		
R10mm (y-2)					0.013***	0.012***		
					[4.151]	[3.539]		
R10mm (y-1) x Energy Utility					-0.013**	-0.014**		
					[-2.148]	[-2.279]		
R10mm (y-2) x Energy Utility					0.007	0.006		
					[0.954]	[0.777]		
R20mm (y-1)							0.031***	0.034***
							[7.232]	[7.822]
R20mm (y-2)							0.023***	0.021***
							[4.487]	[4.159]
R20mm (y-1) x Energy Utility							-0.019*	-0.019*
							[-1.662]	[-1.723]
R20mm (y-2) x Energy Utility							0.013	0.013
							[0.988]	[0.971]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.15: Impact of temperature on the default probability of Agriculture Sector

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with the temperature variables interacted with the agriculture dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. The agriculture dummy equals 1 if the firm is operating in the "Agriculture, forestry, and fishing" industry. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.00341***	0.00310***						
	[7.471]	[6.735]						
Mean temp x Agriculture	-0.00166*	-0.00135						
	[-1.718]	[-1.634]						
anomaly			0.00330***	0.00299***				
			[7.004]	[6.357]				
anomaly x Agriculture			-0.00177*	-0.00128				
			[-1.807]	[-1.466]				
Days above 30					0.00005**	0.00006***		
					[2.419]	[2.872]		
Days above 30 x Agriculture					-0.00006*	-0.00005		
					[-1.779]	[-1.317]		
tx90pETCCDI							0.00025***	0.00025***
							[6.588]	[7.164]
tx90pETCCDI x Agriculture							-0.00016**	-0.00016*
							[-2.144]	[-1.730]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Pricipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.16: Impact of precipitation on the default probability of Agriculture Sector

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the agriculture dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. The agriculture dummy equals 1 if the firm is operating in the "Agriculture, forestry, and fishing" industry. "sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
sdii (y-1)	0.076***	0.079***						
	[6.196]	[6.740]						
sdii (y-2)	0.059***	0.058***						
	[4.970]	[5.234]						
sdii (y-1) x Agriculture	-0.034	-0.043						
	[-1.177]	[-1.442]						
sdii (y-2) x Agriculture	-0.070***	-0.076***						
	[-3.009]	[-3.248]						
R1mm (y-1)			0.005***	0.006***				
			[3.246]	[4.233]				
R1mm (y-2)			0.007***	0.006***				
			[4.208]	[3.110]				
R1mm (y-1) x Agriculture			-0.001	-0.002				
			[-0.389]	[-0.883]				
R1mm (y-2) x Agriculture			0.001	0.001				
			[0.320]	[0.207]				
R10mm (y-1)					0.012***	0.015***		
					[4.632]	[5.912]		
R10mm (y-2)					0.013***	0.012***		
					[4.159]	[3.557]		
R10mm (y-1) x Agriculture					-0.002	-0.005		
					[-0.524]	[-1.080]		
R10mm (y-2) x Agriculture					-0.003	-0.004		
					[-0.449]	[-0.481]		
R20mm (y-1)							0.031***	0.034***
							[7.182]	[7.785]
R20mm (y-2)							0.023***	0.021***
							[4.527]	[4.209]
R20mm (y-1) x Agriculture							-0.016*	-0.020**
							[-1.708]	[-2.093]
R20mm (y-2) x Agriculture							-0.012	-0.012
							[-1.238]	[-1.198]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.17: Impact of temperature on the default probability when GUO is a manager

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with the global ultimate owner (GUO) manager dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "GUO manager" is a dummy that equals 1 if a firm's GUO is also a current manager of the firm. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.157***	0.113***						
	[3.994]	[3.179]						
Mean temp x GUO Manager	-0.180***	-0.161***						
	[-7.372]	[-7.267]						
Anomaly			0.162***	0.118***				
			[3.915]	[3.119]				
Anomaly x GUO Manager			-0.109***	-0.094***				
			[-4.270]	[-4.018]				
Days above 30					0.004*	0.003*		
					[1.807]	[1.840]		
Days above 30 x GUO Manager					-0.011***	-0.011***		
					[-5.073]	[-5.021]		
Tx90p							0.007**	0.007**
							[2.041]	[2.233]
Tx90p x GUO Manager							-0.022***	-0.021***
							[-6.952]	[-6.820]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065
R-squared	0.254	0.259	0.254	0.259	0.254	0.259	0.254	0.259

Table 5.18: Impact of precipitation on the default probability when GUO is a manager

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the global ultimate owner (GUO) manager dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "GUO manager" is a dummy that equals 1 if a firm's GUO is also a current manager of the firm. "sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
sdii (y-1)	0.033**	0.032**						
	[2.349]	[2.502]						
sdii (y-2)	0.035***	0.027**						
	[2.687]	[2.259]						
sdii (y-1) x GUO Manager	-0.031***	-0.027**						
	[-2.621]	[-2.308]						
sdii (y-2) x GUO Manager	-0.038***	-0.035**						
	[-2.684]	[-2.603]						
R1mm (y-1)			0.001	0.002				
			[1.078]	[1.512]				
R1mm (y-2)			0.007***	0.006***				
			[5.244]	[4.662]				
R1mm (y-1) x GUO Manager			-0.006***	-0.006***				
			[-3.870]	[-3.863]				
R1mm (y-2) x GUO Manager			-0.008***	-0.007***				
			[-4.391]	[-4.305]				
R10mm (y-1)					0.004	0.005**		
					[1.414]	[2.116]		
R10mm (y-2)					0.010***	0.008***		
					[3.498]	[2.832]		
R10mm (y-1) x GUO Manager					-0.012***	-0.011***		
					[-4.372]	[-4.129]		
R10mm (y-2) x GUO Manager					-0.013***	-0.012***		
					[-3.779]	[-3.704]		
R20mm (y-1)							0.013***	0.015***
							[2.771]	[3.494]
R20mm (y-2)							0.023***	0.019***
							[4.662]	[4.218]
R20mm (y-1) x GUO Manager							-0.023***	-0.021***
							[-5.231]	[-4.913]
R20mm (y-2) x GUO Manager							-0.026***	-0.025***
							[-4.278]	[-4.310]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065	2,550,065
R-squared	0.254	0.259	0.254	0.259	0.254	0.259	0.254	0.259

Appendices

5.A Figures and Tables

Table 5.A.1: Firm default probability, temperature, and high leverage

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with the high-leverage dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "High leverage" is a dummy that equals 1 when a firm is in the top 20% for its liabilities to total assets ratio. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.308***	0.301***						
	[6.558]	[6.294]						
Mean temp x High leverage	0.163***	0.034						
	[4.785]	[1.169]						
Anomaly			0.276***	0.328***				
			[2.882]	[3.646]				
Anomaly x High leverage			0.219	-0.175				
			[0.662]	[-0.577]				
Days above 30					0.001	0.002		
					[0.350]	[0.889]		
Days above 30 x High leverage					0.027***	0.018***		
					[5.441]	[3.858]		
Tx90p							0.007	0.015**
							[1.206]	[2.589]
Tx90p x High leverage							0.089***	0.050**
							[4.314]	[2.555]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410
R-squared	0.275	0.285	0.270	0.284	0.273	0.284	0.274	0.285

Table 5.A.2: Firm default probability, precipitation, and high leverage

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the high-leverage dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "High leverage" is a dummy that equals 1 when a firm is in the top 20% for its liabilities to total assets ratio. "sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
sdii (y-1)	0.045***	0.045***						
	[3.525]	[3.701]						
sdii (y-2)	0.036***	0.031**						
	[2.717]	[2.454]						
sdii (y-1) x High leverage	0.148***	0.165***						
	[3.654]	[4.326]						
sdii (y-2) x High leverage	0.102***	0.129***						
	[2.946]	[3.906]						
R1mm (y-1)			-0.002	0.001				
			[-0.800]	[0.342]				
R1mm (y-2)			0.009***	0.009***				
			[3.126]	[2.972]				
R1mm (y-1) x High leverage			0.036***	0.027***				
			[3.732]	[2.723]				
R1mm (y-2) x High leverage			-0.007	-0.015				
			[-0.689]	[-1.467]				
R10mm (y-1)					-0.004	-0.000		
					[-0.865]	[-0.018]		
R10mm (y-2)					0.010*	0.009		
					[1.858]	[1.609]		
R10mm (y-1) x High leverage					0.080***	0.076***		
					[5.035]	[4.807]		
R10mm (y-2) x High leverage					0.017	0.016		
					[0.920]	[0.875]		
R20mm (y-1)							0.002	0.005
							[0.383]	[0.768]
R20mm (y-2)							0.013*	0.010
							[1.753]	[1.207]
R20mm (y-1) x High leverage							0.143***	0.147***
							[5.741]	[6.230]
R20mm (y-2) x High leverage							0.051*	0.062**
							[1.909]	[2.381]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410	5,244,410
R-squared	0.275	0.285	0.275	0.285	0.275	0.285	0.275	0.285

Table 5.A.3: Temperature, Manager-owner

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with a global ultimate owner (GUO) dummy and a GUO manager dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "GUO" is a dummy that equals 1 if a firm's GUO is not a manager of the firm. "GUO manager" is a dummy that equals 1 if a firm's GUO is also a current manager of the firm. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.704***	0.664***						
	[4.221]	[3.896]						
Mean temp x GUO	-0.603*	-0.596*						
	[-1.656]	[-1.689]						
Mean temp x GUO Manager	-1.051**	-1.022**						
	[-2.552]	[-2.578]						
Anomaly			0.232	0.211				
			[1.563]	[1.395]				
Anomaly x GUO			0.268	0.251				
			[0.832]	[0.801]				
Anomaly x GUO Manager			0.029	0.013				
			[0.075]	[0.034]				
Days above 30					0.026***	0.026***		
					[3.649]	[3.800]		
Days above 30 x GUO					-0.034**	-0.033**		
					[-2.496]	[-2.517]		
Days above 30 x GUO Manager					-0.057***	-0.055***		
					[-3.969]	[-3.977]		
Tx90p							0.129***	0.126***
							[7.312]	[7.411]
Tx90p x GUO							-0.199***	-0.194***
							[-5.636]	[-5.635]
Tx90p x GUO Manager							-0.237***	-0.228***
							[-7.090]	[-7.111]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.271	0.285

Table 5.A.4: Precipitation, Manger-onwer

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with a global ultimate owner (GUO) dummy and a GUO manager dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "GUO" is a dummy that equals 1 if a firm's GUO is not a manager of the firm. "GUO manager" is a dummy that equals 1 if a firm's GUO is also a current manager of the firm. "sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
sdii (y-1)	0.246***	0.245***						
	[9.055]	[9.299]						
sdii (y-2)	0.233***	0.230***						
	[9.355]	[10.083]						
sdii (y-1) x GUO	-0.349***	-0.341***						
	[-8.294]	[-8.111]						
sdii (y-1) x GUO Manager	-0.350***	-0.341***						
	[-6.812]	[-6.892]						
sdii (y-2) x GUO	-0.360***	-0.355***						
	[-9.180]	[-9.258]						
sdii (y-2) x GUO Manager	-0.364***	-0.359***						
	[-8.179]	[-8.391]						
R1mm (y-1)			0.034***	0.034***				
			[6.323]	[6.630]				
R1mm (y-2)			0.022***	0.020***				
			[3.546]	[3.391]				
R1mm (y-1) x GUO			-0.056***	-0.055***				
			[-6.294]	[-6.271]				
R1mm (y-1) x GUO Manager			-0.062***	-0.060***				
			[-5.548]	[-5.530]				
R1mm (y-2) x GUO			-0.026**	-0.026**				
			[-2.296]	[-2.352]				
R1mm (y-2) x GUO Manager			-0.036***	-0.035***				
			[-2.649]	[-2.686]				
R10mm (y-1)					0.064***	0.065***		
					[8.218]	[9.015]		
R10mm (y-2)					0.049***	0.047***		
					[5.425]	[5.448]		
R10mm (y-1) x GUO					-0.100***	-0.097***		
					[-7.218]	[-7.166]		
R10mm (y-1) x GUO Manager					-0.114***	-0.109***		
					[-6.813]	[-6.759]		
R10mm (y-2) x GUO					-0.068***	-0.068***		
					[-4.082]	[-4.178]		
R10mm (y-2) x GUO Manager					-0.080***	-0.078***		
					[-3.829]	[-3.921]		
R20mm (y-1)							0.127***	0.127***
							[11.829]	[12.407]
R20mm (y-2)							0.094***	0.091***
							[6.637]	[6.845]
R20mm (y-1) x GUO							-0.183***	-0.177***
							[-9.785]	[-9.623]
R20mm (y-1) x GUO Manager							-0.209***	-0.201***
							[-9.639]	[-9.562]
R20mm (y-2) x GUO							-0.130***	-0.128***
							[-5.114]	[-5.208]
R20mm (y-2) x GUO Manager							-0.163***	-0.159***
							[-5.341]	[-5.462]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.271	0.285	0.271	0.285	0.271	0.285

Table 5.A.5: The impact of temperature on the default probability of southern firms

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with temperature variables interacted with the Southern dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Southern" is a dummy that equals 1 if a firm is located either in Italy, Spain, or Portugal. "Anomaly" is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. "Days above 30" is the total number of days in a year that saw temperatures above 30°C. "Tx90p" is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centered around a 5-day interval for the baseline period of 1961-1990. In each specification, we control for precipitation, firm fixed effects, and industry-year fixed effects. In columns 5, 6, 7, and 8, we also control for cold days effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp	0.274***	0.251***						
	[4.089]	[3.721]						
Mean temp x Southern	0.073	0.057						
	[1.111]	[0.901]						
Anomaly			0.318***	0.307***				
			[4.890]	[4.647]				
Anomaly x Southern			-0.016	-0.040				
			[-0.249]	[-0.644]				
Days above 30					0.004	0.005		
					[1.091]	[1.335]		
Days above 30 x Southern					0.000	-0.000		
					[0.097]	[-0.108]		
Tx90p							0.037***	0.041***
							[4.056]	[4.500]
Tx90p x Southern							-0.016	-0.020**
							[-1.605]	[-2.026]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Table 5.A.6: The impact of precipitation on the default probability of southern firms

This table reports the estimated coefficients for the OLS regression of equation (1) and equation (2) with precipitation variables interacted with the Southern dummy. The dependent variable takes a value of 0 if the firm is Active and a value of 1 if it is either Insolvent or Bankrupt. "Southern" is a dummy that equals 1 if a firm is located either in Italy, Spain, or Portugal. "sdii" is the yearly average of daily precipitation sum on wet days, where wet days are defined as daily precipitation sum > 1mm. "R1mm" is the total number of days when daily precipitation sum > 1mm in a year. "R10mm" is the total number of days when daily precipitation sum > 10mm in a year. "R20mm" is the total number of days when daily precipitation sum > 20mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. In columns 2, 4, 6, and 8, we control for firm-level (Leverage, NITA, CATA, AGE) and country-level (GDP, GOVBOND, SOVCDS) control variables. Robust standard errors, clustered at the firm level and industry-year level, are shown in parentheses. The sample period is 2005–2014. The observations are annual. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default Probability							
VARIABLES	1	2	3	4	5	6	7	8
sdii (y-1)	0.044**	0.048**						
	[2.301]	[2.566]						
sdii (y-2)	0.035**	0.033**						
	[1.984]	[2.041]						
sdii (y-1) x Southern	0.039	0.039*						
	[1.644]	[1.692]						
sdii (y-2) x Southern	0.031	0.032*						
	[1.642]	[1.841]						
R1mm (y-1)			0.001	0.001				
			[0.305]	[0.755]				
R1mm (y-2)			0.004	0.002				
			[1.564]	[1.162]				
R1mm (y-1) x Southern			0.008***	0.008***				
			[3.362]	[3.196]				
R1mm (y-2) x Southern			0.006*	0.006				
			[1.731]	[1.597]				
R10mm (y-1)					0.003	0.005		
					[0.824]	[1.280]		
R10mm (y-2)					0.005	0.005		
					[1.182]	[1.036]		
R10mm (y-1) x Southern					0.013***	0.015***		
					[2.976]	[3.206]		
R10mm (y-2) x Southern					0.010*	0.010*		
					[1.739]	[1.704]		
R20mm (y-1)							0.012*	0.014**
							[1.784]	[2.055]
R20mm (y-2)							0.004	0.004
							[0.593]	[0.523]
R20mm (y-1) x Southern							0.024***	0.025***
							[2.755]	[2.919]
R20mm (y-2) x Southern							0.025***	0.023***
							[2.847]	[2.756]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	Yes	No	Yes	No	Yes	No	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Chapter 6

Conclusions and Further Research

6.1 Concluding Remarks

This dissertation contributes to the literature on capital structure and the impact of climate change on corporate sectors, specifically focusing on European small and medium-sized enterprises (SMEs). I explore three interconnected topics: (1) the relationship between SME leverage, firm risk, and ownership structure, aiding in a better understanding of the determinants of SMEs' capital structure and the role of ownership in influencing firm leverage; (2) the adverse effects of global warming on small and micro firms, providing the inaugural study of climate risk for the small-business sector to guide policymakers in addressing climate issues affecting this crucial segment of the global economy; (3) the nexus between climate and default in small and micro firms, with special emphasis on rising temperature and intense precipitation.

The first empirical chapter (Chapter 3) examines the relationship between SME leverage, ownership concentration, and the characteristics of the ultimate owner across 12 European countries. Utilizing an extensive dataset of 625,483 companies - the largest used to date for studying the capital structure of European companies - allows for robust generalization of the findings within the Eurozone economy context. The study confirms a non-linear, inverted U-shaped relationship between ownership concentration and capital structure for both large firms and SMEs and investigates the impact of the ultimate owner type on a firm's capital structure decisions, a novelty in the literature. The study finds family-owned firms to be the most reliant on debt, while government-owned firms use the least. The study further illustrates how firm-specific determinants can exert varying influences on different measures of leverage.

The second empirical chapter (Chapter 4) assesses the impact of climate change, specifically the increase in temperatures, on the performance of small and micro businesses in Europe. Using granular weather data from E-OBS and financial reports from Orbis, matched through geocoding, the study reveals a decrease in a firm's operating income by 6.8% for every 1°C increase in average temperature. This effect is significantly pronounced in micro firms, suggesting that vulnerability to climate change is inversely proportional to firm size. Additionally, financially constrained firms appear more adversely impacted by temperature shocks, indicating that limited access to external finance could impede a firm's adaptive capacity to climate risk. Finally, the study documents heterogeneous industry and ownership effects with respect to the detrimental impact of hot weather. Energy and utility firms demonstrate improved performance under higher temperatures, potentially due to climate-induced demand increase. Family-owned businesses show less impact from rising temperatures, while government-controlled firms exhibit no sensitivity to temperature shocks.

The final empirical chapter (Chapter 5) explores how increasing temperature and intensive precipitation affect the default probability of European small and micro firms. The data, free of survivorship bias, include both active and inactive firms up to 2015. The firms' bankruptcy history is compiled from the status change and the date of this change. Diverging from a focus on large corporations, the study underscores the vulnerability of small and micro firms to physical risks. This study represents the first to use real default events to investigate climate risk for small firms, specifically, the implications of rising temperature and heightened precipitation. We find that a one standard deviation increase in mean temperature and the simple intensity index can respectively raise a firm's default probability by 86.5 and 32.4 basis points, which are economically significant impacts. As stated by Ou et al. (2018), an average default rate rise by 27 basis points could lead to a rating downgrade from Aaa to Baa.

6.2 Further Research

While the empirical test in Chapter 3 covers a substantial portion of European SMEs, further studies would benefit from improved ownership data. One limitation of Chapter 3 lies in the absence of time-varying ownership data to adequately control for time-invariant variables. Some might argue the necessity of time-varying ownership data is minimal, as ownership structure tends to be stable for SMEs, particularly for family-owned enterprises exhibiting high ownership concentration — a prevalent characteristic among our studied firms. However, future research investigating shock events to SME owners may provide stronger grounds for establishing a causal relationship between changes in ownership structure and leverage choices.

Regarding the studies in Chapters 4 and 5, they are solely focused on the chronic physical risks faced by SMEs. Potential further research could integrate detailed natural disaster data, specifically data pertaining to weather-related extreme events, to examine their direct and indirect effects on SMEs in hazard-prone areas. Researchers could also explore whether the negative impact diminishes as the distance between firms and the central location of the events increases. Concerning the adverse impacts of climate change on firm performance, we do not differentiate between a demand mechanism (lower operating income due to decreased demand) or a firm-productivity channel (reduced firm-level productivity with higher temperatures) owing to data limitations. However, the lessened negative impacts in the energy and utility sectors might suggest the role of demand dynamics.

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