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Rain or shine, default risks align: exploring the climate-default nexus in small and micro firms

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ABSTRACT

We investigate the impact of escalating temperatures and heavy rainfall on the default probability of small and micro enterprises (SMiEs) in six European countries between 2005 and 2014. Our findings reveal that a one standard deviation increase (2.56°C) in the yearly mean temperature raises a firm's default probability by 86.5 basis points. Additionally, a one standard deviation increase (2.46 mm) in the Simple Precipitation Intensity Index increases the default probability by 32.4 basis points. We argue that one channel explaining the adverse impact of climate risk on default probability is labour productivity loss. In addition, micro and financially constrained firms exhibit increased vulnerability to these risks. However, when the ultimate owners also serve as the firms' managers, they can mitigate the adverse effects of rising temperatures and heavy rainfall.

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1. Introduction

The adverse effects of climate change are being experienced by individuals and corporations globally. Over the past decade, devastating floods have affected a number of countries, resulting in numerous fatalities and substantial economic damage. Concurrently, extremely hot summers have become a recurring phenomenon (Morit 2022; NASA 2022). These drastic weather changes are inextricably tied to global warming (Herring et al. 2018). A warmer climate causes increased evaporation, leading to higher overall precipitation as well as more intense rainfall episodes and flash floods. Consequently, the frequency of extreme weather events is likely to escalate as global temperatures continue to rise (IPCC 2023). Given the significant disruption of climate risk on economies, businesses, and livelihoods, climate-related topics have been a key focus of academic research (Nordhaus 2007). In this paper, we examine the impact of two prominent effects of climate change – rising temperatures and increased precipitation risks – on the default probability of small and micro European firms.

The literature on climate risk and firm outcomes has largely focussed on large, publicly listed firms, examining effects on stock returns or accounting performance. Seminal contributions such as Addoum, Ng, and Ortiz-Bobea (2020) and Pankratz, Bauer, and Derwall (2023) document that temperature shocks affect firm performance, but do not study realised default events. We contribute to this literature by providing the first systematic evidence on how increasing temperatures and rainfall affect default probabilities of small and micro enterprises (SMiEs) in Europe.

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A limitation of existing work on climate-related credit risk is the scarcity of observed default data, particularly for smaller firms. As a result, prior studies rely on indirect measures of firm riskiness, including Merton's Distance to Default (Capasso, Gianfrate, and Spinelli 2020; Kabir et al. 2021; Q. Nguyen, Diaz-Rainey, and Kuruppuarachchi 2023) or bank loan spreads (Javadi and Masum 2021). In contrast, we use firm-level information on realised default events from the Orbis database and directly estimate the effect of weather shocks on default outcomes. This approach moves beyond implied risk measures and enables identification of the impact of climate conditions on credit risk using observed defaults.

The health of the small business sector is integral to the prosperity and stability of many countries. In 2022, SMiEs constituted 99.0% of the number of enterprises in the non-financial business sector (NFBS) in the EU-27, employing around 64 million people, or 39.4% of total NFBS employment. Their economic significance is highlighted by their contribution of 43.7% of the NFBS's total value-added.[1] Despite this, 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 degree longitude by 0.1 degree latitude, are carefully matched to the headquarters address of each firm in our dataset. The localised operations of small businesses justify our decision to proxy firm-level physical risk using temperature and precipitation data for their headquarters. This reduces the measurement error that inevitably arises in large firm studies (Addoum, Ng, and Ortiz-Bobea 2020; Custodio et al. 2025; Pankratz, Bauer, and Derwall 2023; Pankratz and Schiller 2024).

We expand climate risk research beyond performance to survival, demonstrating how small enterprises' underperformance due to climate risk can ultimately result in bankruptcy. Regarding the rising-temperature risk, our findings suggest a 1°C increase in the yearly mean temperature can increase a firm's default probability by 33.7 basis points. As for the precipitation risk, a one standard deviation increase in the Simple Daily Intensity Index can raise the default probability by 32.4 basis points. These results are both statistically and economically significant. To put it into context, if we were analysing larger rated firms, according to Moody's Investors Service (2017), 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.

We add to previous studies by testing several channels through which climate shocks affect default risk. Identifying these mechanisms is crucial for policy design and financial stability, as it highlights where targeted adaptation measures and stress-testing frameworks should focus to strengthen the resilience of SMiEs.

Firstly, we study the effects on labour-intensive firms. Extreme heat and heavy precipitation reduce worker efficiency by inducing heat stress, fatigue, and cognitive decline (Burke, Hsiang, and Miguel 2015; Dunne, Stouffer, and John 2013; Parsons et al. 2021; Somanathan et al. 2021), as well as by disrupting outdoor labour, logistics, and infrastructure (Liu et al. 2018; Verschuur, Koks, and Hall 2023). Experimental and observational evidence shows that worker performance deteriorates sharply at high temperatures (Hancock, Ross, and Szalma 2007; Seppanen, Fisk, and Lei 2006), and firm-level data document substantial productivity losses on hot days (Somanathan et al. 2021). Infrastructure disruptions further amplify these effects by impairing transportation and network reliability (Liu et al. 2018). While large firms can often mitigate productivity shocks by reallocating staff across tasks or locations, adopting remote working arrangements, or drawing on geographically diversified operations, SMiEs typically operate with lean workforces and concentrated activities, making it far more challenging to substitute for lost labour input. Consistent with this mechanism, we find that labour-intensive firms experience more than double the increase in default probability following temperature and precipitation shocks relative to non-labour-intensive firms.

Secondly, we analyse differences in firms' financial ability to absorb and adapt to climate shocks. Smaller firms, highly leveraged firms, and financially constrained firms face larger increases in default probability when exposed to extreme temperatures and intense rainfall. Prior work shows that larger firms can mitigate climate risks through relocation, infrastructure investment, production adjustments, and insurance coverage (Berkhout, Hertin, and Gann 2006; Hoffmann et al. 2009), as well as by relying on financial buffers and organisational resilience (Hollnagel, Woods, and Leveson 2006; Huang et al. 2022; Linnenluecke, Griffiths, and Winn 2008; Vogus and Sutcliffe 2007). The limited financial flexibility of SMiEs helps explain why temperature effects are muted for large U.S. firms (Addoum, Ng, and Ortiz-Bobea 2020) but are pronounced for small and micro firms in our sample. We focus on small firms and find that smaller and less financially resourced firms are more vulnerable to climate change. Our results show that the yearly mean temperature measure predicts an additional increase of 16.4% in the default probability of micro firms relative to small firms. Regarding the precipitation index, we observe that the effect on the default probability of 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 rainfall.

Thirdly, we document substantial heterogeneity across industries, concentrated in the energy and agriculture sectors. The energy sector appears relatively insulated from heat-related risk, reflecting its greater ability to adapt operations and mitigate exposure, while the agriculture sector displays distinct sensitivities due to its direct dependence on climatic conditions.

Finally, we document that governance plays a role: when the ultimate owner is directly involved in management, the increase in default probability associated with climate shocks is significantly attenuated. This pattern is consistent with stronger incentives and greater commitment by owner-managers to implement adaptive measures and safeguard firm survival compared to firms not run by owner-managers.

The remainder of this paper is structured as follows. Section 2 reviews the literature on the effects of climate risk on corporate performance. Section 3 describes the data and presents summary statistics. Section 4 outlines the empirical methodology and defines the variables. Section 5 presents the baseline empirical findings, while Section 6 discusses robustness tests. Finally, Section 7 concludes and discusses the implications of our findings.

2. Related literature

This paper relates to several strands of the literature linking climate risk to corporate outcomes and credit risk. Existing studies primarily focus on large, publicly listed firms and rely on indirect measures of risk rather than observed default events.

A first strand examines how climate risk affects the pricing of corporate credit. Prior work shows that firms exposed to physical or transition climate risks face higher bond yields and bank loan spreads, reflecting lenders' reassessment of borrower risk. Using ESG scores, Apergis, Poufinas, and Antonopoulos (2022) document lower bond spreads and higher credit ratings for firms with stronger ESG profiles. Other studies proxy physical climate risk using natural disasters or drought exposure and find higher loan spreads or reduced credit supply for exposed firms (Correa et al. 2022; Faiella and Natoli 2019; Huang et al. 2022; Javadi and Masum 2021; Jung, Herbohn, and Clarkson 2018). While informative about pricing responses, this literature infers default risk indirectly and does not observe realised firm defaults.

A second strand studies climate risk and firm-level default risk using market-based proxies. Because default events are rare among large listed firms, these studies rely on Merton-type distance-to-default measures derived from equity prices. Using U.S. listed firms, D. T. T. Nguyen, Huynh, and Phan (2023) find that climate exposure extracted from earnings calls (Sautner et al. 2023) reduces distance to default, with stronger effects for financially distressed and carbon-intensive firms. Related evidence shows that climate risk or low ESG scores increase default risk when measured using market-based measures (Huang et al. 2022; Li, Zhang, and Zhao 2022). By construction, however, these approaches exclude small and micro firms and do not rely on observed default events.

Our analysis also connects to research on climate risk in the banking sector. Using the Billion-Dollar Weather and Climate Disasters Data (NOAA 2025), studies document that climate disasters increase systemic risk and induce banks to reduce lending and increase loan loss provisions (Conlon et al. 2024; Curcio, Gianfrancesco, and Vioto 2023). Climate stress-testing exercises, such as the ECB economy-wide stress test (ECB 2021), assess the impact of physical risk on non-financial corporate default probabilities and bank resilience. However, these frameworks rely on default models calibrated on listed firms using distance-to-default measures and therefore do not capture the vulnerability of small and micro firms.

Finally, a large literature documents that extreme temperatures and precipitation adversely affect firm performance, revenues, and profits (Addoum, Ng, and Ortiz-Bobea 2020, 2023; Cathcart et al. 2025; Kumar and

Parikh 2001; Pankratz, Bauer, and Derwall 2023; Pankratz and Schiller 2024; Rao et al. 2022). While these studies establish economically meaningful performance effects, they do not examine whether such shocks ultimately translate into firm default.

Our contribution is to bridge these strands of the literature by providing the first systematic evidence on how temperature and precipitation shocks affect realised default events of small and micro enterprises in Europe. By focussing on observed defaults rather than pricing-based or market-implied risk measures, and by studying firms that are central to the European economy but largely absent from existing work, we offer new evidence on the credit risk implications of physical climate risk.

3. Data and summary statistics

3.1. Sample and variables

We obtain firm-level financial and ownership data for European SMiEs from Moody's Bureau van Dijk Orbis for the period 2005–2014. Firms are classified as micro (total assets up to €2 million) or small (total assets between €2 and €10 million), following European Commission definitions, using total assets due to limited coverage of headcount and turnover in Orbis. We retain firm-year observations with valid industry and accounting information.

Following Cathcart et al. (2020), we exclude firm-year observations with missing information on either the firm's default status or the date at which the status is recorded. We further drop observations with ambiguous status classifications, including active branch, active dormant, active reorganisation, inactive branch, inactive no precision, dissolved demerger, dissolved merger, dissolved takeover, and cases with unknown status, as these categories do not allow a clear assessment of firms' financial health. In line with standard corporate finance practice, non-profit organisations, financial, and public sector firms are excluded.[2] At the country level, we drop countries with fewer than 5000 firm-year observations and those exhibiting unreliable default reporting. To identify the latter, we compute the share of active firm-year observations by country and exclude countries where this share exceeds 99.99%, which indicates inadequate recording practices (for example, missing dates of status changes). After applying these filters, the final sample comprises approximately 5.2 million firm-year observations (0.85 million firms) across six European countries: the United Kingdom, Italy, France, Spain, Portugal, and Belgium. These countries include four of the five largest European economies, ensuring broad representativeness of European SMiEs.[3]

The sample period predates the 2015 Paris Agreement and the subsequent tightening of climate-related regulation. While climate policies were already in place during this period, their economic bite was weaker than post-2015, allowing us to study firms' exposure to physical climate risk before widespread regulatory and disclosure changes (Bolton and Kacperczyk 2021; Carbone et al. 2022; Costola and Vozian 2025; Ginglinger and Moreau 2023; Monasterolo and De Angelis 2020). Although not policy-neutral, this setting reduces confounding from policy-induced firm adjustments and provides a baseline for assessing fundamental climate exposure.[4]

Weather data are drawn from the E-OBS dataset (version v23.1e), a high-resolution gridded dataset of daily temperature and precipitation observations constructed from meteorological stations across Europe. The dataset covers land areas between latitudes 25° and 71.5° North and longitudes 25° West and 45° East, with records available from 1950 onward. We use a fine spatial grid of 0.1° longitude by 0.1° latitude, corresponding to grid cells of approximately 3.5 km × 11 km at northern latitudes (around 71.5°N) and 10.1 km × 11 km at southern latitudes (around 25°N). A key advantage of this version is that it includes annual climate indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI), which provide standardised measures of temperature and precipitation extremes and are directly used in our empirical analysis.

Firm locations are geocoded using the postcode of each firm's headquarters and converted into latitude and longitude coordinates. Each firm is then matched to the nearest E-OBS grid cell by minimising the geographic distance between the firm's coordinates and the centre of surrounding weather cells, yielding firm-specific, location-year climate exposures. Given the geographically concentrated operations of small and micro firms, this approach provides precise firm-level exposure measures and mitigates the measurement error that arises when

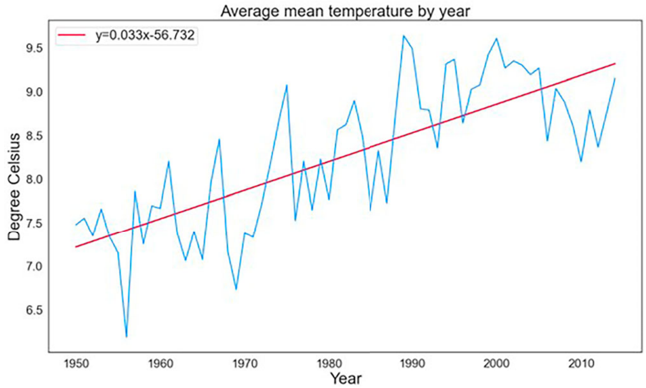

Figure 1. Mean temperature in Europe from 1950 to 2014.

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

assigning weather exposure to larger, geographically diversified firms (Addoum, Ng, and Ortiz-Bobea 2020; Pankratz, Bauer, and Derwall 2023). The matching procedure is described in detail in the first section of the Internet Appendix.

We capture both chronic and acute physical climate risks using a set of temperature and precipitation indicators constructed from daily weather observations. Temperature exposure is measured using four variables.

The first measure is *Mean temp*, the yearly mean temperature computed as the average value of daily mean temperatures over a year. The second measure is *Anomaly1*, 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. The third measure is *Days above 30*, the total number of days above 30°C in a year. The fourth measure is *Max Temp 90%*, the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature. In particular, we define TX_{ij} as the highest temperature recorded on day i in year j. Meanwhile, $TX_{in}90$ denotes the 90th percentile of daily maximum temperature, centred around a 5-day interval, for the baseline period of 1961–1990. The percentage of instances where $TX_{ij} > TX_{in}90$ for each sample year is then calculated (Zhang et al. 2005).

Precipitation risk is measured using four ETCCDI indices derived from daily rainfall data. The first measure is *Av. Daily rain – w/d*, the Simple Precipitation Intensity Index which is calculated using the sum of daily precipitation on wet days divided by the number of wet days in a year. Wet days are defined as days with daily precipitation $>$ 1 mm. The second measure is *Rainy Days* $>$ 1 mm, the total number of days when daily precipitation $>$ 1 mm in a year. The third measure is *Rainy Days* $>$ 10 mm, the total number of days when daily precipitation $>$ 10 mm in a year. The fourth measure is *Rainy Days* $>$ 20 mm, the total number of days when daily precipitation $>$ 20 mm in a year.

In regressions of temperature risk, we control for average precipitation and, when using hot-day measures, for cold-day exposure. Conversely, in precipitation regressions, we control for mean temperature. Our weather measures are comparable to those used in Addoum, Ng, and Ortiz-Bobea (2020), Pankratz, Bauer, and Derwall (2023), and Pankratz and Schiller (2024), while benefiting from finer spatial resolution.

Figure 1 plots the evolution of location-specific mean temperatures across Europe using E-OBS data from 1950 to 2014. The figure shows a clear upward trend in yearly mean temperatures, with an average increase of approximately 2.1°C over the period. This magnitude exceeds the frequently cited 1.5°C benchmark reported in the media, reflecting our focus on land-only surface temperature data. Because land has a lower heat capacity than oceans, it warms more rapidly when additional heat is absorbed into the climate system (Byrne 2020). Figure 2 displays temperature anomalies for the sample period (2003–2014), where the predominance of red-shaded regions indicates that temperatures were persistently above historical local averages throughout the period of investigation.

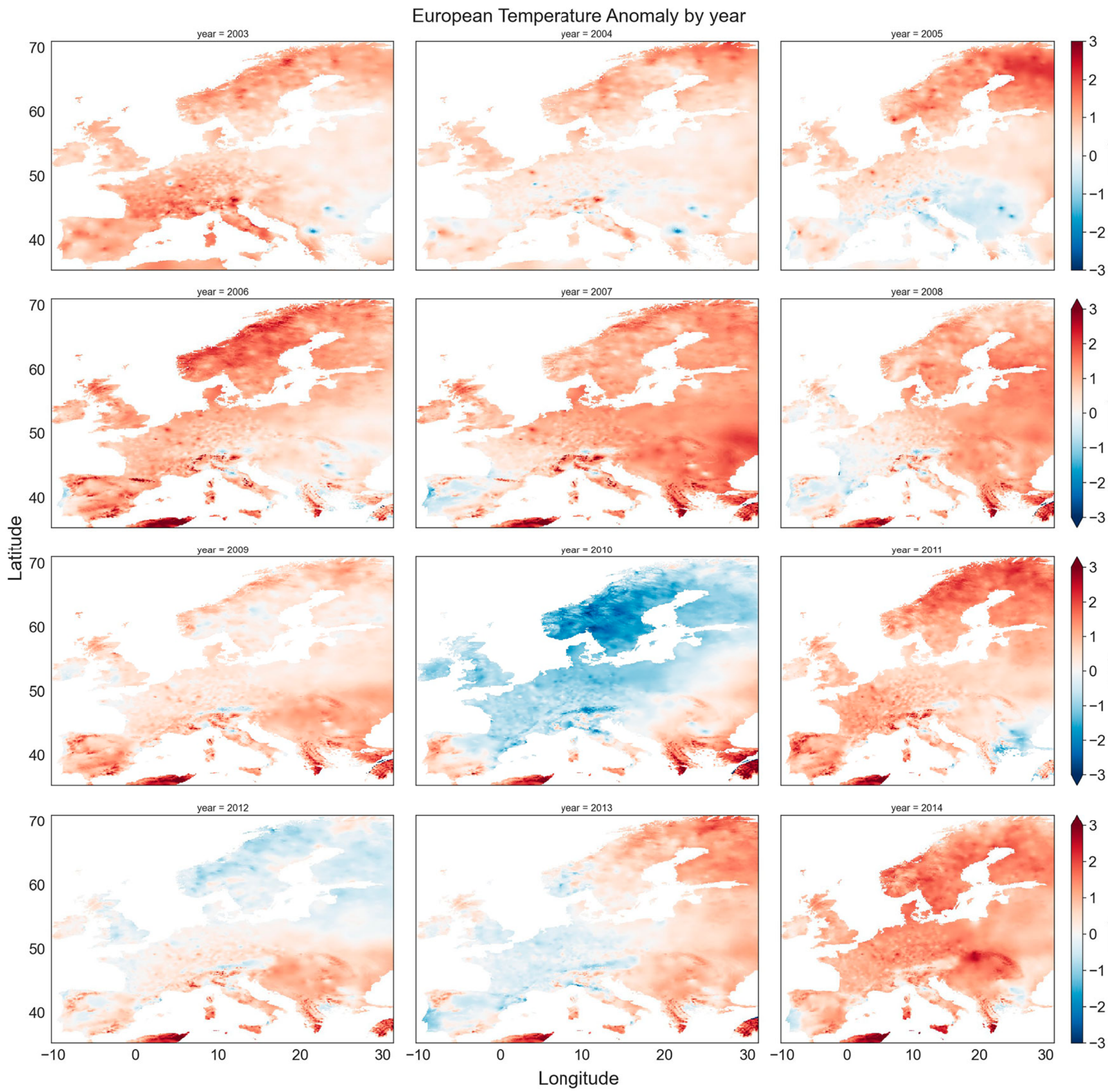

Figure 2. Temperature anomaly in Europe by year, 2003–2014.

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.

As a robustness check, we include standard firm-level controls following Cathcart et al. (2020), namely total liabilities to total assets (*Leverage*), net income to total assets (*Nita*), current assets to total assets (*Cata*), and firm age (*Age*). Firm-level accounting variables are winsorized at the 1st and 99th percentiles within each country. We also include country-year macroeconomic controls, comprising the natural logarithm of GDP growth from Eurostat (*Gdp*), 3-month government bond yields from the IMF World Economic Outlook (*Govbond*), and the log of sovereign CDS spreads from Markit (*Sovcds*).

3.2. Summary statistics

Table 1 reports the number of insolvent and bankrupt firms by year. Default rates peak in the aftermath of the global financial crisis and the European sovereign debt crisis, particularly in 2009, 2012, and 2013. From 2008

Table 1. Number of defaults.

Years	Overall sample		Micro Firms		Small Firms		α
	N.	(%)	N.	(%)	N.	(%)	
2006	6108	1.35	3566	1.26	2542	1.50	0.839
2007	6922	1.39	4036	1.32	2886	1.50	0.879
2008	10, 204	1.93	6099	1.89	4105	2.00	0.947
2009	13, 311	2.45	8531	2.60	4780	2.22	1.172
2010	11, 861	2.15	7249	2.17	4612	2.12	1.019
2011	12, 629	2.24	7954	2.33	4675	2.10	1.113
2012	14, 670	2.57	9347	2.70	5323	2.35	1.149
2013	14, 809	2.58	9345	2.68	5464	2.43	1.100
2014	12, 158	2.16	7534	2.21	4624	2.07	1.067
2015	6737	1.40	4174	1.47	2563	1.30	1.129
Average	10, 947	2.02	6784	2.06	4157	1.96	1.041

Note: 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 sub-samples: 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 €2 million, it is classified as a small corporation. The table displays the number (and percentage for each sub-sample) 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.

Table 2. Summary statistics of control variables.

VARIABLES	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
Average Employee Cost	32.451	24.454	25.417	1.035	347.410

Note: 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. Average Employee Cost is the ratio of total employee cost (in thousand euros) to the number of employees. The sample period is 2005–2014.

onward, micro firms consistently exhibit higher default rates than small firms. For descriptive completeness, this table includes firms with only one observed year. By construction, such firms are excluded from regressions with firm fixed effects. Summary statistics reported in Table 3 are therefore computed using the firm-year observations included in the baseline regression sample.

Table 2 presents a comprehensive summary of the control variables utilised in the regression analysis. Micro firms constitute the majority, accounting for 60.8% of all observations in the entire sample. On average, micro and small firms rely on 71.1% of liabilities to finance their operations. The average age of firms in our sample is 16.8 years. However, it is important to note that this variable has a large standard deviation, indicating a wide range of firm ages, with the minimum being less than one year and the maximum exceeding 100 years. The median GDP growth rate is 0.652%, while the average 3-month government bond yield for the given sample period is 1.75%.

Table 3 presents the summary statistics of temperature and precipitation measures. The mean annual temperature in our sample is 13.6°C, with a standard deviation of 2.6°C. Both temperature anomalies are positive, providing clear evidence of a global warming trend. For robustness, we apply an alternative method to compute

Table 3. Summary statistics of weather variables.

VARIABLES	Mean	Median	SD	Min	Max
Mean temp	13.606	13.551	2.566	−2.138	20.991
Anomaly1	0.370	0.392	1.000	−4.492	4.987
Anomaly2	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
Max Temp 90%	20.835	19.452	7.755	0.548	79.178
Min Temp 10%	6.969	6.301	4.527	0.000	46.575
Av. Daily rain	2.034	1.952	0.790	0.258	8.690
Av. Daily rain – w/d	8.209	8.084	2.455	3.730	23.918
Rainy Days > 1 mm	92.826	96.000	31.346	18.000	249.000
Rainy Days > 10 mm	23.325	21.000	11.597	1.000	111.000
Rainy Days > 20 mm	6.784	6.000	5.460	0.000	51.000

Note: 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. 'Anomaly1' is the difference between the mean temperature and the average mean temperature of the past 30 years in the same location. 'Anomaly2' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centred around a 5-day interval for the baseline period of 1961–1990. 'Min Temp 10%' is the percentage of days with daily minimum temperature < 10th percentile of daily minimum temperature centred around a 5-day interval for the baseline period of 1961–1990. 'Av. Daily rain' is the average daily precipitation in mm in a year. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days in a year, where wet days are defined as daily precipitation sum > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. The sample period is 2005–2014.

the temperature anomalies (*Anomaly2*). Rather than subtracting the 30-year rolling mean temperature from current temperatures, we subtract the 30-year mean temperature computed for the period from 1974 to 2003, which 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, *Max Temp 90%*, is 20.8%, while the value for the cold days' measure, *Min Temp 10%*, is 7.0%. 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 distribution of temperatures has shifted towards warmer conditions. For precipitation measures, the summary statistics also behave as expected. The number of intense precipitation days decreases as we adopt more stringent definitions, i.e. moving from *Rainy Days* > 1 mm to *Rainy Days*> 20 mm.

4. Methodology

We estimate the default probability by employing a panel linear probability model with fixed effects. We follow the approach used by Dell, Jones, and Olken (2014), who advocate using pooled OLS regression coupled with firm fixed effects and industry-year fixed effects to estimate the impact of weather variables. Since the temperature at a firm' s location may be correlated with the firm's specific business plan, industry characteristics, and year trends, incorporating these fixed effects enables us to isolate temperature shocks within the same firm location and industry-year, identifying their causal impact on firm default probability. A key assumption behind this approach is that short-term weather fluctuations around the local average are plausibly exogenous and can be treated as quasi-random.

Moreover, there is a growing consensus in the literature about the use of weather variables as instruments or exogenous shocks in empirical social science research. Mellon (2021), for example, provides a comprehensive review and concludes that while weather variables are not perfectly exogenous, they are widely accepted as relatively exogenous sources of variation in many settings. This strengthens the credibility of our identification strategy, particularly for short-term temperature anomalies, which are unlikely to be systematically related to unobserved firm-level factors.

To address any remaining endogeneity concerns and establish causality, we lag our climate risk proxies. Additionally, introducing multiple fixed effects significantly reduces the risk of omitted variable bias.

Although the ordinary least squares (OLS) estimates are unbiased and consistent, the estimated standard errors are not because of heteroscedasticity in the residuals. Thus, we estimate robust standard errors. We use two-way clustered standard errors at both firm and industry-year levels. For the second cluster, we use 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 discussed in Addoum, Ng, and Ortiz-Bobea (2020), two-way clustered standard errors are more robust than standard errors clustered solely at the firm level or adjusted for spatial correlations. In particular, we model default probability using the following two equations:

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

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

Equation (1) serves as our reference model, where i, j, and t indicate a specific company, sector, and year respectively. The *DefaultState* variable is a dummy indicating corporate insolvency status. It takes a value of 0 for solvent firms and 1 for firms undergoing bankruptcy or insolvency procedures. θ_i represents $firm_i$ fixed effects, while $\theta_{j,t}$ is the $industry_j$-$year_t$ fixed effect. Given that a firm's head office weather conditions, including temperature and precipitation, may correlate with its specific business strategies, industrial characteristics, and annual trends, we include these distinct controls for each firm and industry-year. This allows us to causally evaluate the impact of climate risk on default probability. Our key hypothesis assumes that weather variables are randomly distributed and exogenously determined, as in Auffhammer et al. (2013), Pankratz, Bauer, and Derwall (2023) and Dell, Jones, and Olken (2014).

$T_{i,t}$ and $P_{i,t}$ represent firm-specific temperature and precipitation exposures. Given that changes in temperature and precipitation are likely to affect corporate bankruptcies with some delay (Barrot and Sauvagnat 2016; Pankratz, Bauer, and Derwall 2023), we include weather variables with two lags. Following the climate literature (see, for example, Auffhammer et al. 2013), we incorporate precipitation when analysing the effects of rising temperatures to control for the historical correlation between precipitation and temperature in the same location. Similarly, we control for temperature when assessing the risks associated with precipitation. Our challenge is to establish a causal link between local weather variations and potential financial repercussions on firms which eventually may lead to corporate bankruptcy. Corporations often require an extended period to navigate the bankruptcy procedure following a negative shock, especially when the shock constitutes an incremental (rather than acute) manifestation of a physical risk.

In Equation (1), we follow the approach of Addoum, Ng, and Ortiz-Bobea (2020), Pankratz, Bauer, and Derwall (2023) and Pankratz and Schiller (2024), and do not include any firm or country time-varying control variables to address the so-called 'over-controlling' or 'bad controls' issue (Angrist and Pischke 2009). There is a trade-off between the 'bad controls' issue and the 'omitted variables' issue. Additionally, we estimate Equation (2) as a robustness check by including firm-year and country-year control variables as in Cathcart et al. (2020). Our findings remain largely unaltered. For the control variables in Equation (2), we follow Cathcart et al. (2020) and use lagged values. As for our primary variable of interest, the temperature and precipitation exposures, we include two lags in our main tests.

Table 4. The impact of temperature on firm default probability (two lags).

	Default Status							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp (t-1)	0.049	0.029						
	[0.847]	[0.486]						
Mean temp (t-2)	0.281***	0.239***						
	[5.678]	[4.657]						
Anomaly1 (t-1)	0.011			0.031				
			[0.525]	[0.176]				
Anomaly1 (t-2)	0.232***			0.274***				
			[5.385]	[4.447]				
Days above 30 (t-1)					−0.003	−0.004*		
					[−1.301]	[−1.677]		
Days above 30 (t-2)					0.005**	0.005**		
					[2.228]	[2.567]		
Max Temp 90% (t-1)							−0.008	−0.009
							[−1.351]	[−1.485]
Max Temp 90% (t-2)							0.021***	0.021***
							[5.432]	[5.601]
Leverage		0.073***		0.074***		0.073***		0.074***
		[15.906]		[15.910]		[15.899]		[15.906]
Nita		−0.131***		−0.131***		−0.131***		−0.131***
		[−14.419]		[−14.418]		[−14.424]		[−14.420]
Cata		0.011***		0.011***		0.011***		0.011***
		[7.000]		[6.992]		[6.966]		[6.994]
Age		0.001**		0.001**		0.001**		0.001**
		[2.513]		[2.519]		[2.549]		[2.550]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	No	No	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,244,420	5,242, 980
R-squared	0.270	0.284	0.270	0.284	0.270	0.284	0.270	0.284

Note: This table reports the estimated coefficients for the OLS regression of Equations (1) and (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. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centred 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 additionally control for firm-level (Leverage, Nita, Cata, Age) and country-level (Gdp, Govbond, Sovcds) control variables. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

5. Results

5.1. Heat exposure, precipitation exposure and default probability

Tables 4 and 5 report the estimated results for our heat and precipitation measures from Equation (1) and Equation (2). In the baseline specification (Equation (1)), we deliberately exclude supplementary firm-level control variables to avoid the risk of 'over-controlling.' Following Equation (2), columns 2, 4, 6, and 8 introduce additional firm-level control variables as well as country-year macroeconomic variables to test whether these controls affect the results. Specifically, we include the key determinants of firms' default probability identified in Cathcart et al. (2020) to validate the estimates presented in columns 1, 3, 5, and 7.

The inclusion of these additional variables does not change our initial findings, confirming their robustness. Generally, firms with higher leverage (as measured by *Leverage*) and lower profitability (as measured by net income to total assets, *Nita*) are more likely to default, which aligns with standard expectations in the

Table 5. The impact of precipitation on firm default probability.

	Default Status							
VARIABLES	1	2	3	4	5	6	7	8
Av. Daily rain – w/d (t-1)	0.075***	0.078***						
	[6.271]	[6.803]						
Av. Daily rain – w/d (t-2)	0.057***	0.057***						
	[4.931]	[5.182]						
Rainy Days > 1 mm (t-1)	0.006***			0.005***				
			[3.308]	[4.293]				
Rainy Days > 1 mm (t-2)	0.006***			0.007***				
			[4.328]	[3.178]				
Rainy Days > 10 mm (t-1)					0.012***	0.015***		
					[4.718]	[6.002]		
Rainy Days > 10 mm (t-2)					0.013***	0.012***		
					[4.235]	[3.604]		
Rainy Days > 20 mm (t-1)							0.030***	0.034***
							[7.270]	[7.862]
Rainy Days > 20 mm (t-2)							0.023***	0.021***
							[4.586]	[4.251]
Leverage		0.074***		0.074***		0.073***		0.073***
		[15.913]		[15.916]		[15.907]		[15.908]
Nita		−0.131***		−0.131***		−0.131***		−0.131***
		[−14.413]		[−14.412]		[−14.420]		[−14.416]
Cata		0.011***		0.011***		0.011***		0.011***
		[6.935]		[6.998]		[6.998]		[6.966]
Age		0.001**		0.001**		0.001**		0.001**
		[2.442]		[2.483]		[2.509]		[2.465]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Macros	No	Yes	No	Yes	No	Yes	No	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

Note: This table reports the estimated coefficients for the OLS regression of Equations (1) and (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. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm 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 additionally control for firm-level (Leverage, Nita, Cata, Age) and country-level (Gdp, Govbond, Sovcds) control variables. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

default risk literature. In the subsequent tests, we follow Dell, Jones, and Olken (2014), Addoum, Ng, and Ortiz-Bobea (2020), Pankratz, Bauer, and Derwall (2023), and Pankratz and Schiller (2024), and present results without including control variables.

As shown in Table 4, only the heat measures lagged by two years exhibit a statistically significant positive impact on a firm's default probability. Conversely, in Table 5, both the one-year and two-year lagged precipitation measures emerge as statistically significant factors that increase the default probability of a firm. Therefore, when analysing precipitation risk in subsequent sections, we incorporate both lags. Instead, for the heat risk analysis, we only employ the two-year lagged heat measures in the remainder of the study.

Table 6 exhibits the results for two-year lagged heat risk. We find a 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 increases the default probability by 86.5 basis points. We observe similar findings when we employ temperature anomaly as a proxy for global warming rather than the level of mean temperature, with a one standard deviation increase in the temperature anomaly leading to a 32.6 basis points increase in default probability. Looking at 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.

Table 6. The impact of temperature on firm default probability (one lag).

	Default Status			
VARIABLES	1	2	3	4
Mean temp (t-2)	0.337***			
	[7.545]			
Anomaly1 (t-2)		0.326***		
		[7.067]		
Days above 30 (t-2)			0.005**	
			[2.405]	
Max Temp 90% (t-2)				0.024***
				[6.627]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.270	0.270	0.270

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) with lagged two-year 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. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centred 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 3 and 4, we also control for cold days effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

Given that adaptation to absolute high 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 that a one standard deviation increase in the percentage of days above the 90th percentile raises the default probability by 18.6 basis points. These increased default probabilities are consistent with the findings of the ECB (2021) comprehensive climate stress test. The test assumes that in the absence of interventions to mitigate climate risks, the financial consequences for businesses arising from extreme weather conditions could significantly escalate, potentially having a detrimental impact on their creditworthiness.

Table 5 presents the findings related to precipitation risk. In line with the baseline results for heat risk, we consistently observe a persistent positive effect of precipitation risk on a firm's default probability. It is noteworthy that both the one-year and two-year lagged precipitation measures make significant contributions to the heightened probability of default. With respect to the simple precipitation intensity index, a one standard deviation increase leads to a 32.4 basis points rise in the default probability. For the number of heavy rainfall days, we observe more pronounced positive effects when adopting more rigorous precipitation measures. An additional day when daily rainfall exceeds 1 mm, 10 mm, and 20 mm increases the default probability by 1.2, 2.5, and 5.3 basis points respectively.

Our findings above are statistically and economically meaningful. To put it into context, if we were analysing larger rated firms, Moody's Investors Service (2017) suggest that a 27 basis points rise in the probability of default can lead to a downgrade from Aaa to Baa, converting an investment-grade borrower into a speculative-grade one. Our observations regarding the impacts of heat and precipitation risks on default probability are also consistent with findings on climate disasters (Huang et al. 2022).

Table 7. Quarterly NUTS3-level floods and heatwaves from 2003–2012.

VARIABLES	Observations	Mean	Median	SD	Min	Max
Flood Freq	21,120	0.102	0	0.378	0	5
Flood	21,120	0.081	0	0.272	0	1
Heatwave Freq	21,120	0.029	0	0.175	0	2
Heatwave	21,120	0.028	0	0.166	0	1

Note: Note: This table presents the summary statistics of quarterly NUTS3 level floods and heatwaves in Belgium, Spain, France, United Kingdom, Italy, and Portugal from 2003–2012. Flood dummy equals 1 if the NUTS3 region experienced at least one flood event. Flood Freq captures the total number of flood events at the NUTS3 region. Heatwave dummy equals 1 if the NUTS3 region experienced at least one heatwave event. Heatwave Freq captures the total number of heatwave events at the NUTS3 region.

5.1.1. Baseline robustness

Weather variables can be treated as quasi-random, as documented in Dell, Jones, and Olken (2014). Indeed, recent influential studies on the impact of temperature on firm performance – such as Addoum, Ng, and Ortiz-Bobea (2020), Pankratz, Bauer, and Derwall (2023), and Pankratz and Schiller (2024) – follow Dell, Jones, and Olken (2014) in estimating the effects of heat exposure using rich fixed-effect models. These studies argue that, after controlling for location and industry-year fixed effects, the causal impact of heat exposure can be identified. However, relying solely on within-location-industry variation in weather variables may still leave estimates vulnerable to unobserved shocks correlated with both climate exposure and firm outcomes.

To test the robustness of our baseline results, we use two meteorological hazards as exogenous shocks to proxy for temperature and precipitation measures. Specifically, we use heatwaves as a proxy for extreme temperature risk and floods as a proxy for extreme rainfall risk. The heatwave and flood data are sourced from the Risk Data Hub (RDH) of the European Commission's Joint Research Centre (Faiella et al. 2020). The RDH provides detailed records of natural disasters, including the type of hazard, the date of occurrence, and the affected local areas, classified at the NUTS3 level.[5]

Because meteorological hazards are extreme and relatively rare events, we construct heatwave and flood dummy variables to indicate whether a disaster occurred at a given NUTS3 location within the two-year window prior to the firm's accounting date. In addition, we construct continuous measures, the Heatwave Freq and the Flood Freq, to capture the total number of events in the two years preceding each observation date.

Table 7 reports quarterly summary statistics of the two meteorological hazards from the RDH dataset in Belgium, Spain, France, the United Kingdom, Italy, and Portugal. The sample period spans 2003–2012, corresponding to the two years preceding our main firm-level data (2005–2014). In total, the dataset contains 21,120 observations (528 NUTS3 regions × 40 quarters). We find that floods are considerably more frequent than heatwaves: within a single quarter, a NUTS3 region can experience up to five floods but only two heatwaves.

Table 8 presents the regression results of meteorological hazards at default risk, using the baseline Equation 2, where we replace weather variables with flood and heatwave measures. Consistent with our baseline results in Tables 4 and 5, we find that both extreme heat exposure (proxied by Heatwave) and extreme rainfall (proxied by Flood) significantly increase the default probability of SMiEs. The effect of heatwaves is weaker than that of floods, likely because heatwaves occur less frequently. For example, as shown in Table 7, the average quarterly frequency of heatwaves is 0.029, compared with 0.102 for floods. In general, using meteorological hazards as exogenous shocks strengthens confidence in the validity of our baseline findings.

Additionally, we perform eight distinct placebo tests, one for each specification in Tables 4 and 5. For each test, we replace the actual values of the independent variable with random numbers drawn from a normal distribution defined by the mean and standard deviation of that variable at the country-industry-year level. This process is repeated for both the independent variable and its lagged value. We then estimate Equation (1) using the randomised independent variable and its lagged counterpart, repeating the procedure 500 times for each independent variable. The resulting distributions of placebo coefficients are displayed in Figures IA.1 and IA.2. In all cases, the placebo coefficients are centred around zero, while the estimated coefficients reported in Tables 4 and 5, which are denoted in the Figures as dashed red lines, consistently fall outside the range of the placebo estimates.

Table 8. The impact of heatwaves and floods on firm default probability.

	Default Status			
VARIABLES	1	2	3	4
Heatwave	0.125*			
	[1.776]			
Heatwave Freq		0.087*		
		[1.707]		
Flood			0.081**	
			[2.306]	
Flood Freq				0.043***
				[2.987]
Leverage	0.074***	0.074***	0.074***	0.074***
	[15.943]	[15.945]	[15.950]	[15.938]
Nita	−0.131***	−0.131***	−0.131***	−0.131***
	[−14.359]	[−14.356]	[−14.352]	[−14.352]
Cata	0.011***	0.011***	0.011***	0.011***
	[6.899]	[6.906]	[6.926]	[6.921]
Age	0.001**	0.001**	0.001**	0.001**
	[2.535]	[2.531]	[2.521]	[2.512]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	No	No
Temperature	No	No	Yes	Yes
Country Macros	Yes	Yes	Yes	Yes
Observations	5,198,628	5,198,628	5,198,628	5,198,628
R-squared	0.283	0.283	0.283	0.283

Note: This table reports the estimated coefficients for the OLS regression of Equation (2). We replace the heat and precipitation measures with heatwave and flood measures from RDH. 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. Heatwave dummy equals 1 if the firm's NUTS3 region experienced a heatwave event in the previous two years. Heatwave Freq captures the total number of heatwave events in the previous two years. Flood dummy equals 1 if the firm's NUTS3 region experienced a flood event in the previous two years. Flood Freq captures the total number of flood events in the previous two years. In each specification, we control for firm fixed effects, and industry-year fixed effects. In columns 1 and 2, we control for precipitation effects. In columns 3 and 4, we control for temperature effects. We also additionally control for firm-level (Leverage, Nita, Cata, Age) and country-level (Gdp, Govbond, Sovcds) control variables. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

5.2. Labour productivity channel

The observed increase in default probability due to temperature and precipitation risk may be attributable to reductions in labour productivity. From a physiological standpoint, elevated temperatures negatively influence worker efficiency by inducing heat-related discomfort, fatigue, and reduced cognitive function (Burke, Hsiang, and Miguel 2015; Dunne, Stouffer, and John 2013; Parsons et al. 2021; Somanathan et al. 2021). These effects compromise the ability to sustain normal levels of physical and mental performance. For instance, research has shown that exceeding a core body temperature of 38°C can impair both physical capacity and cognitive clarity, heightening the risk of accidents and work-related fatigue (Kjellstrom, Holmer, and Lemke 2009). Evidence also suggests that even moderate increases in indoor temperatures–particularly above 25°C–can reduce productivity. For example, Seppanen, Fisk, and Faulkner (2003) report a 2% drop in performance per 1°C rise above this threshold, while Niemelä et al. (2002) document a 1.8% decline per degree within the 22−−29°C range in call centre environments. Graff Zivin and Neidell (2014) further show that outdoor workers tend to reduce their working day significantly- up to one hour – on particularly hot days due to heat fatigue.

Operationally, extreme weather can disrupt firm activities by halting outdoor labour, delaying logistics, or damaging infrastructure. Heavy precipitation and flooding, for instance, can prevent agricultural activities like planting and harvesting or disrupt transportation and construction, leading to costly downtime (Kjellstrom, Holmer, and Lemke 2009).

A natural consequence of climate-related productivity shocks could be an increase in the effective cost of labour. For a given salary, lower efficiency caused by heat stress or rainfall disruptions reduces output per worker. Consider a simple example: during a heatwave, workers in a small firm may produce 20% less in their standard 8-hour shift. To meet deadlines and client commitments, the firm may need to compensate for the shortfall by asking employees to work longer hours, often at premium overtime rates, or by hiring temporary replacement workers. In such cases, lower productivity translates directly into higher average costs per employee.

To test this mechanism empirically, we adapt our baseline regression by replacing the dependent variable with Average Employee Cost. Table 9 reports the results. Columns 1–4 examine heat risk, while columns 5–8 focus on rainfall risk. Consistent with our hypothesis, we find that higher climate risk significantly raises per-employee costs. Specifically, a one standard deviation increase in yearly mean temperature increases average employee cost by €962.6 (375.14 × 2.566), equivalent to a 3.9% rise relative to the median value of €24,454 in our sample. Similar results emerge for temperature anomalies and for the percentage of days above the 90th percentile. Turning to rainfall risk, we also find significant positive effects, though with smaller magnitudes: for instance, a one standard deviation increase in the number of rainy days above 20 mm raises employee costs by approximately 0.5% of the median (€20.49 × 5.46/24,454). These findings provide direct evidence that climate shocks increase the effective cost of labour, consistent with the mechanism that reduced worker productivity raises labour expenses and, ultimately, default risk.

We then investigate whether temperature and precipitation events disproportionately impact labour productivity, potentially affecting labour-intensive firms more significantly. To this end, we categorise a firm as labour-intensive based on the ratio of its labour costs to its total assets. Firms with a labour-intensiveness ratio in the top 20% are assigned a 'labour-intensive' dummy variable of 1. This variable is then interacted with our baseline regression to test the hypothesis.

Table 10 details the results related to temperature risks. Although the temperature anomaly in column 2 does not have a statistically significant interaction coefficient, the remaining three temperature risk measures are statistically significant when interacted with the labour-intensive dummy. For the mean temperature measure, the default risk for labour-intensive firms increases by 8.6% compared to non-labour-intensive firms (0.028%/0.325%). We call this type of effect the 'relative effect'. In absolute terms, the default probability increased by 7.2 basis points (0.028% × 2.566) for a one standard deviation increase in mean temperature, which equates to 3.6% (0.072%/2.02%) of the average default rate in the sample. We refer to this as the 'absolute effect'. The findings are even more pronounced for the number of hot days measures (columns 3 and 4), where the relative labour effects exceed 100%, and the coefficients for the interaction terms are statistically significant at the 1% level. The absolute labour effect for the number of days above 30°C variable is 21.9 basis points (27.332 × 0.008%) or 10.8% (0.219%/2.02%) of the average default rate in the sample. As for the top 90% hot days measure, the absolute labour effect is 17.8 basis points (7.755 × 0.023%) or 8.8% (0.178%/2.02%) of the mean default rate.

Similarly, Table 11 reports the results for precipitation-related physical risks, showing a consistent trend where labour-intensive firms are more susceptible to precipitation risks across all measures. For the precipitation intensity index in column 1, the relative labour effect is 107.5% ((0.062 + 0.053)/(0.06 + 0.047)). The effect is smaller for rainy days above 1 mm (column 2) at 70% (0.007%/(0.007% + 0.003%)) and stronger for days with heavier rains, that is 194.1% (column 3) and a 141.5% (column 4). The absolute labour effects are 28.2 basis points ((0.053% + 0.062%) × 2.455), 21.9 basis points (0.007% × 31.346), 38.3 basis points ((0.022% + 0.011%) × 11.597), and 31.7 basis points ((0.038% + 0.020%) × 5.46) for models 1 to 4 respectively, which equate to 14.0%, 10.8%, 19.0% and 15.7% of the mean default rate in the sample, respectively.

5.3. *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 limits their ability to secure the funding necessary for managing climate risks.

Table 9. The impact of temperature and precipitation on average employee cost.

	Average Employee Cost							
VARIABLES	1	2	3	4	5	6	7	8
Mean temp (t-1)	0.375***							
	[4.770]							
Anomaly1 (t-1)		0.401***						
		[5.008]						
Days above 30 (t-1)			−0.001					
			[−0.326]					
Max Temp 90% (t-1)				0.017*				
				[1.810]				
Av. Daily rain – w/d (t-1)					0.034**			
					[2.432]			
Rainy Days > 1 mm (t-1)						0.002		
						[0.485]		
Rainy Days > 10 mm (t-1)							0.009*	
							[1.798]	
Rainy Days > 20 mm (t-1)								0.020***
								[3.042]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	No	No	No	No
Cold days	No	No	Yes	Yes	No	No	No	No
Temperature	No	No	No	No	Yes	Yes	Yes	Yes
Observations	3,328,752	3,328,752	3,328,752	3,327,467	3,328,752	3,328,752	3,328,752	3,328,752
R-squared	0.711	0.711	0.711	0.711	0.711	0.711	0.711	0.711

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) by replacing the dependent variable with Average Employee Cost (in thousand euros). The dependent variable Average Employee Cost is the ratio of total employee cost to total number of employees. 'Mean temperature' is the average daily mean temperature over the year. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature > 90th percentile of daily maximum temperature centred around a 5-day interval for the baseline period of 1961–1990. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. In each specification, we control for firm fixed effects, and industry-year fixed effects. In columns 1 – 4, we control for precipitation effects. In columns 5 – 8, we control for temperature effects. In columns 3 and 4, we also control for cold days effects. T-values based on 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.

Unlike large corporations, SMiEs are unable to redistribute resources among different factories and business segments when faced with extreme weather events, as highlighted by Custodio et al. (2025). This suggests that firm size is a considerable factor that may lead to differential 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 that we interact with the weather variables. Table 12 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. The relative micro firms effect is 16.4% while the absolute effect is 13.3 basis points or 6.6% of the average default rate in the sample. When looking at the default rate sensitivity to the relative number of hot days, micro firms exhibit an approximately doubled default probability compared to small firms. The absolute micro firm effect for the number of days above 30°C is 43.7 basis points or 21.6% of the average default rate. Finally, the impact of the number of days above 30°C on the default probability is only statistically significant for micro firms.

Table 13 reports the results for precipitation risk. For the simple precipitation intensity index, we observe an 86.5% relative micro firm effect and an absolute effect of 18.9 basis points or 9.4% of the mean default rate. These effects for the number of days when daily precipitation exceeds 20 mm are 52.4% (relative) and 12.0 basis points or 5.9% of the mean default rate (absolute).

Next, we examine the hypothesis that financially constrained firms might face more pronounced impacts from climate risk. This is attributed to their limited financial resources, which can hinder their ability to

Table 10. The impact of temperature on the default probability of labour intensive firms.

	Default Status			
VARIABLES	1	2	3	4
Mean temp (t-2)	0.325***			
	[6.689]			
Mean temp (t-2) × Labour-intensive	0.028**			
	[2.446]			
Anomaly1 (t-2)		0.340***		
		[5.661]		
Anomaly1 (t-2) × Labour-intensive		−0.082		
		[−0.916]		
Days above 30 (t-2)			0.004*	
			[1.662]	
Days above 30 (t-2) × Labour-intensive			0.008***	
			[3.497]	
Max Temp 90% (t-2)				0.021***
				[5.267]
Max Temp 90% (t-2) × Labour-intensive				0.023***
				[3.418]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes
Observations	4,743,970	4,743,970	4,743,970	4,743,970
R-squared	0.272	0.272	0.272	0.272

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) with temperature variables interacted with the Labour-intensive 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. 'Labour-intensive' equals 1 if the firm lies in the top 20% of the ratio of its labour cost and total asset. 'Mean temperature' is the average daily mean temperature over the year. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centred 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 3 and 4, we also control for cold days effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

implement climate adaptation measures. We adopt the methodology of Schauer, Elsas, and Breitkopf (2019) to generate a dummy variable indicating a firm's financially constrained status. Unlike other financial constraint measures (SA index by Hadlock and Pierce 2010; KZ index by Baker, Stein, and Wurgler 2003) used for large firms, Schauer, Elsas, and Breitkopf (2019) built this measure specifically for private European firms, making it particularly apt for our dataset of European small and micro firms. This financial constraint indicator 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, Elsas, and Breitkopf (2019), firms in the top 20% of the financially constrained score distribution are defined as financially constrained firms.

Table 14 reports our tests for the default risk impact of heat risk on financially constrained firms. The relative effect on the probability of default for constrained firms is 21.4%, and the absolute effect is 13.6 basis points, which equates to 6.7% of the average default rate. 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. The absolute effect for the relative hot days' measure is 9.6% of the mean default rate.

Table 15 presents the outcomes for precipitation risk. We consistently observe that financially constrained firms are more negatively affected (higher default probability) by intense precipitation (10 mm or more). For intense rainfall (20 mm), we find that the relative effects for financially constrained firms are 1.4 times larger

Table 11. The impact of precipitation on the default probability of labour intensive firms.

	Default Status			
VARIABLES	1	2	3	4
Av. Daily rain – w/d (t-1)	0.060***			
	[5.056]			
Av. Daily rain – w/d (t-2)	0.047***			
	[4.051]			
Av. Daily rain – w/d (t-1) × Labour-intensive	0.053**			
	[2.480]			
Av. Daily rain – w/d (t-2) × Labour-intensive	0.062***			
	[3.630]			
Rainy Days > 1 mm (t-1)		0.003*		
		[1.748]		
Rainy Days > 1 mm (t-2)		0.007***		
		[3.791]		
Rainy Days > 1 mm (t-1) × Labour-intensive		0.007**		
		[2.179]		
Rainy Days > 1 mm (t-2) × Labour-intensive		−0.002		
		[−0.628]		
Rainy Days > 10 mm (t-1)			0.007***	
			[2.825]	
Rainy Days > 10 mm (t-2)			0.010***	
			[3.102]	
Rainy Days > 10 mm (t-1) × Labour-intensive			0.022***	
			[3.440]	
Rainy Days > 10 mm (t-2) × Labour-intensive			0.011*	
			[1.886]	
Rainy Days > 20 mm (t-1)				0.022***
				[5.047]
Rainy Days > 20 mm (t-2)				0.019***
				[3.632]
Rainy Days > 20 mm (t-1) × Labour-intensive				0.038***
				[3.909]
Rainy Days > 20 mm (t-2) × Labour-intensive				0.020**
				[2.138]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Temperature	Yes	Yes	Yes	Yes
Observations	4,743,970	4,743,970	4,743,970	4,743,970
R-squared	0.272	0.272	0.272	0.272

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) with precipitation variables interacted with the Labour-intensive 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. 'Labour-intensive' equals 1 if the firm lies in the top 20% of the ratio of its labour cost and total asset. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

than those for financially healthy firms. The absolute effect for rainy days above 20 mm is 30.6 basis points or 15.1% of the mean default rate.

5.4. Industry effects

The differential impact of weather across industries has been documented in several studies. For instance, Addoum, Ng, and Ortiz-Bobea (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 (2024), Custodio et al. (2025), and Graff Zivin and Neidell (2014) find heat-sensitive industry firms

Table 12. The impact of temperature on the default probability of micro firms.

	Default Status			
VARIABLES	1	2	3	4
Mean temp (t-2)	0.317***			
	[6.921]			
Mean temp (t-2) × Micro	0.052***			
	[5.226]			
Anomaly1 (t-2)		0.316***		
		[5.555]		
Anomaly1 (t-2) × Micro		0.029		
		[0.674]		
Days above 30 (t-2)			0.003	
			[1.122]	
Days above 30 (t-2) × Micro			0.005***	
			[2.967]	
Max Temp 90% (t-2)				0.016***
				[3.595]
Max Temp 90% (t-2) × Micro				0.016***
				[4.391]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.270	0.270	0.270

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) 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. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centred 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 3 and 4, we also control for cold days effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

are more negatively impacted by heat exposure. In this section, we concentrate on two particular sectors: energy and agriculture, both of which need to be separately studied according to previous economic climate literature.

We consolidate the energy sectors into a dummy variable and interact it with heat and precipitation measures. Columns 1–4 of Panel A in Tables 16 and 17 present the results for heat risk and precipitation risk, respectively. We find consistent evidence suggesting the energy sector is less impacted by heat risk except for the mean temperature measure. The energy sector's default probability is 78% lower than that for other sectors when subject to a temperature anomaly (column 2). The absolute effect of temperature anomaly is 25.6 basis points, which equates to 12.7% of the average default rate. For the number of hot days' effects, we observe that the negative impacts on default probability are nullified for the energy sector. Regarding precipitation risk, there is no evidence to show that the energy sector behaves differently from other sectors.

We also interact the agriculture industry dummy with the weather variables in the baseline model, with results reported in Columns 5–8 of Panel A in Tables 16 (heat risk) and 17 (precipitation risk). While labour-intensive industries generally suffer under rising heat as we show in the previous section, agriculture presents an added layer of complexity as its outputs depend directly on weather. Prior work (e.g. Hsiang et al. 2017; Kim and Escap 2012) shows that higher temperatures and elevated CO_2 levels can enhance yields through extended growing seasons, CO_2 fertilisation, and reduced cold stress. Consistent with this, we find that small and micro agricultural firms in Europe appear less adversely affected by rising temperatures, and in some cases benefit

Table 13. The impact of precipitation on the default probability of micro firms.

	Default Status			
VARIABLES	1	2	3	4
Av. Daily rain – w/d (t-1)	0.053***			
	[4.289]			
Av. Daily rain – w/d (t-2)	0.036***			
	[2.871]			
Av. Daily rain – w/d (t-1) × Micro	0.039***			
	[3.150]			
Av. Daily rain – w/d (t-2) × Micro	0.038***			
	[3.004]			
Rainy Days > 1 mm (t-1)		0.004**		
		[2.463]		
Rainy Days > 1 mm (t-2)		0.005***		
		[3.075]		
Rainy Days > 1 mm (t-1) × Micro		0.001		
		[0.768]		
Rainy Days > 1 mm (t-2) × Micro		0.003*		
		[1.802]		
Rainy Days > 10 mm (t-1)			0.010***	
			[3.266]	
Rainy Days > 10 mm (t-2)			0.007**	
			[2.579]	
Rainy Days > 10 mm (t-1) × Micro			0.004	
			[1.319]	
Rainy Days > 10 mm (t-2) × Micro			0.010***	
			[3.116]	
Rainy Days > 20 mm (t-1)				0.026***
				[4.976]
Rainy Days > 20 mm (t-2)				0.016***
				[2.966]
Rainy Days > 20 mm (t-1) × Micro				0.009*
				[1.658]
Rainy Days > 20 mm (t-2) × Micro				0.013**
				[2.375]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Temperature	Yes	Yes	Yes	Yes
Observations	5,244,420	5,244,420	5,244,420	5,244,420
R-squared	0.270	0.270	0.270	0.270

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) 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. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

from these offsetting effects. Regarding precipitation, we estimate a 51.2% lower relative default probability for agriculture firms compared to other industries when considering average daily rainfall, with an absolute effect of 17.2 basis points (8.5% of the average default rate). There is also weak evidence that intense precipitation (days above 20 mm) reduces agricultural default risk.

The manufacturing and retail sectors represent a significant portion of our dataset, accounting for nearly 50% of all firm-year observations. It is worthwhile to explore these two sectors individually. Columns 1–4 of Panel B in Tables 16 and 17 present the results for manufacturing firms, while Columns 5–8 of Panel B in Tables 16 and 17 report the findings for the retail sector. In our baseline regressions, we find that, on average, the default

Table 14. Firm default probability, temperature, and financial constraints.

	Default Status			
VARIABLES	1	2	3	4
Mean temp (t-2)	0.248***			
	[4.763]			
Mean temp (t-2) × Constrained	0.053***			
	[3.874]			
Anomaly1 (t-2)		0.252***		
		[3.256]		
Anomaly1 (t-2) × Constrained		−0.015		
		[−0.075]		
Days above 30 (t-2)			0.003	
			[1.144]	
Days above 30 (t-2) × Constrained			0.007***	
			[4.093]	
Max Temp 90% (t-2)				0.011**
				[2.056]
Max Temp 90% (t-2) × Constrained				0.025**
				[2.452]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes
Observations	3,229,318	3,229,318	3,229,318	3,229,318
R-squared	0.291	0.290	0.291	0.291

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) with temperature variables interacted with the dummy (Constrained) 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. 'Constrained' equals 1 when it is in the top 20% for its Schauer, Elsas, and Breitkopf (2019) score. 'Mean temperature' is the average daily mean temperature over the year. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centred 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 3 and 4, we also control for cold days effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

probability of firms in our sample increases following extreme heat and heavy rainfall events. Given that nearly half of the sample comprises manufacturing and retail firms, it is reasonable to expect that these two sectors substantially contribute to the overall baseline effects.

Our sector-specific regressions support this expectation. Although the interaction term between the manufacturing dummy and extreme heat days is statistically significant, most of the other interaction terms for both manufacturing and retail sectors remain insignificant. This suggests that, overall, the climate risk impact on these sectors is comparable to that on other industries.

Interestingly, we observe that manufacturing firms exhibit a slightly lower default probability during periods of extreme heat compared to firms in other sectors. One possible explanation is that manufacturing activities are often conducted indoors, where firms can better control the working environment. This contrasts with sectors like construction or retail, where operations may be more exposed to outdoor conditions and thus more vulnerable to temperature extremes.

5.5. Manager-Owner

We then explore how the 'agency problem' between firm owners and management (Jensen 1986) can influence a firm's response to climate risk. When owners also serve as managers, they face greater exposure to firm-specific risks due to their personal wealth investment and professional skills vested in the company. As Brisley, Cai, and

Table 15. Firm default probability, precipitation, and financial constraints.

	Default Status			
VARIABLES	1	2	3	4
Av. Daily rain – w/d (t-1)	0.076***			
	[6.660]			
Av. Daily rain – w/d (t-2)	0.036**			
	[2.479]			
Av. Daily rain – w/d (t-1) × Constrained	−0.013			
	[−0.427]			
Av. Daily rain – w/d (t-2) × Constrained	0.059**			
	[2.501]			
Rainy Days > 1 mm (t-1)		0.004**		
		[2.243]		
Rainy Days > 1 mm (t-2)		0.006***		
		[2.920]		
Rainy Days > 1 mm (t-1) × Constrained		0.007		
		[1.514]		
Rainy Days > 1 mm (t-2) × Constrained		0.005		
		[1.054]		
Rainy Days > 10 mm (t-1)			0.011***	
			[3.841]	
Rainy Days > 10 mm (t-2)			0.008*	
			[1.932]	
Rainy Days > 10 mm (t-1) × Constrained			0.010	
			[1.253]	
Rainy Days > 10 mm (t-2) × Constrained			0.020**	
			[2.409]	
Rainy Days > 20 mm (t-1)				0.027***
				[5.616]
Rainy Days > 20 mm (t-2)				0.013**
				[1.990]
Rainy Days > 20 mm (t-1) × Constrained				0.022*
				[1.710]
Rainy Days > 20 mm (t-2) × Constrained				0.034***
				[2.773]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Temperature	Yes	Yes	Yes	Yes
Observations	3,229,318	3,229,318	3,229,318	3,229,318
R-squared	0.291	0.291	0.291	0.291

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) with precipitation variables interacted with the dummy (Constrained) 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. 'Constrained' equals 1 when it is in the top 20% for its Schauer, Elsas, and Breitkopf (2019) score. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

Nguyen (2021) suggest, this situation can potentially reduce their risk tolerance, leading to a greater need for climate-related risk mitigation. Furthermore, Huang et al. (2022) demonstrate that diverse managerial strategies can significantly alleviate a company's financial challenges when addressing climate change. Based on these insights, we hypothesise that firms with active involvement of their ultimate owner in day-to-day management can reduce the probability of default compared to firms managed solely by a professional manager. Utilising the ownership data from Orbis, we define a subsample in which all firms are controlled by a Global Ultimate Owner (GUO). Our threshold to define a GUO is an ownership of 50.01% or more of the firm's equity (for more details,

Table 16. Impact of temperature on default probability across sectors.

VARIABLES	Energy sector				Agriculture sector			
Panel A	1	2	3	4	5	6	7	8
Mean temp (t-2)	0.338***				0.341***			
	[7.528]				[7.471]			
Mean temp (t-2) x Industry	−0.209				−0.166*			
	[−1.524]				[−1.718]			
Anomaly1 (t-2)		0.328***				0.330***		
		[7.058]				[7.004]		
Anomaly1 (t-2) x Industry		−0.256**				−0.177*		
		[−2.018]				[−1.807]		
Days above 30 (t-2)			0.005**				0.005**	
			[2.433]				[2.419]	
Days above 30 (t-2) x Industry			−0.014**				−0.006*	
			[−2.564]				[−1.779]	
Max Temp 90% (t-2)				0.025***				0.025***
				[6.630]				[6.588]
Max Temp 90% (t-2) x Industry				0.024***				−0.016**
				[−3.413]				[−2.144]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes	No	No	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	0.270	0.270	0.270	0.270	0.270	0.270	0.270
Panel B	Manufacturing sector				Retail sector			
Mean temp (t-2)	0.368***				0.310***			
	[7.823]				[6.308]			
Mean temp (t-2) x Industry	−0.145				0.089			
	[−1.226]				[0.844]			
Anomaly1 (t-2)		0.354***				0.309***		
		[7.138]				[6.029]		
Anomaly1 (t-2) x Industry		−0.125				0.057		
		[−1.028]				[0.516]		
Days above 30 (t-2)			0.008***				0.004*	
			[3.159]				[1.658]	
Days above 30 (t-2) x Industry			−0.010**				0.005	
			[−2.124]				[1.019]	
Max Temp 90% (t-2)				0.028***				0.021***

(*continued*).

Table 16. Continued.

Panel B	Manufacturing sector				Retail sector			
				[7.246]				[5.553]
Max Temp 90% (t-2) x Industry				−0.016*				0.011
				[−1.929]				[1.251]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes	No	No	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	0.270	0.270	0.270	0.270	0.270	0.270	0.270

Note: This table reports OLS estimates of Equation (1), interacting temperature variables with sectoral dummy variables for the energy (Panel A Columns 1–4), agriculture (Panel A Columns 5–8), manufacturing (Panel B Columns 1–4), and retail (Panel B Columns 5–8) sectors. The dependent variable equals 1 if a firm is Insolvent or Bankrupt and 0 if Active. 'Anomaly1' is the deviation of the yearly mean temperature from its 30-year rolling average at the same location. 'Days above 30' is the annual number of days with temperatures above 30 °C. 'Max Temp 90%' is the percentage of days with daily maximum temperature exceeding the 90th percentile, defined using a centred 5-day window over the 1961–1990 baseline. All specifications include firm fixed effects, industry-year fixed effects, and precipitation controls; columns (3) and (4) additionally control for cold-day exposure. T-statistics based on two-way clustered standard errors at the firm and industry-year level are reported in brackets. The sample period is 2005–2014. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Coefficients are expressed in percentage terms.

Table 17. Impact of precipitation on default probability across sectors.

VARIABLES	Energy sector				Agriculture sector			
Panel A	1	2	3	4	5	6	7	8
Av. Daily rain – w/d (t-1)	0.075***				0.076***			
	[6.219]				[6.196]			
Av. Daily rain – w/d (t-2)	0.057***				0.059***			
	[4.881]				[4.971]			
Av. Daily rain – w/d (t-1) x Industry	0.048				−0.034			
	[0.864]				[−1.177]			
Av. Daily rain – w/d (t-2) x Industry	0.045				−0.070***			
	[0.926]				[−3.009]			
Rainy Days > 1 mm (t-1)		0.005***				0.005***		
		[3.280]				[3.246]		
Rainy Days > 1 mm (t-2)		0.007***				0.007***		
		[4.282]				[4.208]		
Rainy Days > 1 mm (t-1) x Industry		0.002				−0.001		
		[0.374]				[−0.389]		
Rainy Days > 1 mm (t-2) x Industry		0.006				0.001		
		[1.162]				[0.320]		
Rainy Days > 10 mm (t-1)			0.012***				0.012***	
			[4.704]				[4.632]	
Rainy Days > 10 mm (t-2)			0.013***				0.013***	
			[4.180]				[4.159]	
Rainy Days > 10 mm (t-1) x Industry			−0.003				−0.002	
			[−0.356]				[−0.524]	
Rainy Days > 10 mm (t-2) x Industry			0.019				−0.003	
			[1.614]				[−0.449]	
Rainy Days > 20 mm (t-1)				0.030***				0.031***
				[7.240]				[7.182]
Rainy Days > 20 mm (t-2)				0.023***				0.023***
				[4.529]				[4.527]
Rainy Days > 20 mm (t-1) x Industry				−0.004				−0.016*
				[−0.240]				[−1.708]
Rainy Days > 20 mm (t-2) x Industry				0.025				−0.012
				[1.125]				[−1.238]
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	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	0.270	0.270	0.270	0.270	0.270	0.270	0.270

(*continued*).

Table 17. Continued.

Panel A	1	2	3	4	5	6	7	8
	Manufacturing sector				Retail sector			
Panel B	1	2	3	4	5	6	7	8
Av. Daily rain – w/d (t-1)	0.075***				0.073***			
	[6.114]				[5.557]			
Av. Daily rain – w/d (t-2)	0.050***				0.056***			
	[3.744]				[4.369]			
Av. Daily rain – w/d (t-1) x Industry	−0.003				0.005			
	[−0.093]				[0.179]			
Av. Daily rain – w/d (t-2) x Industry	0.033				0.003			
	[1.266]				[0.128]			
Rainy Days > 1 mm (t-1)		0.006***				0.005***		
		[3.318]				[2.858]		
Rainy Days > 1 mm (t-2)		0.007***				0.007***		
		[4.008]				[4.447]		
Rainy Days > 1 mm (t-1) x Industry		−0.003				−0.001		
		[−1.084]				[−0.214]		
Rainy Days > 1 mm (t-2) x Industry		−0.001				−0.001		
		[−0.189]				[−0.277]		
Rainy Days > 10 mm (t-1)			0.014***				0.012***	
			[4.922]				[4.255]	
Rainy Days > 10 mm (t-2)			0.012***				0.013***	
			[3.746]				[3.978]	
Rainy Days > 10 mm (t-1) x Industry			−0.008				0.002	
			[−1.470]				[0.271]	
Rainy Days > 10 mm (t-2) x Industry			0.002				−0.001	
			[0.306]				[−0.084]	
Rainy Days > 20 mm (t-1)				0.033***				0.031***
				[7.708]				[6.351]
Rainy Days > 20 mm (t-2)				0.022***				0.022***
				[4.034]				[3.987]
Rainy Days > 20 mm (t-1) x Industry				−0.012				−0.001
				[−1.110]				[−0.104]
Rainy Days > 20 mm (t-2) x Industry				0.005				0.003
				[0.395]				[0.224]
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry-Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*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	0.270	0.270	0.270	0.270	0.270	0.270	0.270

Table 18. Impact of temperature on the default probability when the GUO is a manager.

	Default Status			
VARIABLES	1	2	3	4
Mean temp (t-2)	0.157***			
	[3.994]			
Mean temp (t-2) × GUO Manager	−0.180***			
	[−7.372]			
Anomaly1 (t-2)		0.162***		
		[3.915]		
Anomaly1 (t-2) × GUO Manager		−0.109***		
		[−4.270]		
Days above 30 (t-2)			0.004*	
			[1.807]	
Days above 30 (t-2) × GUO Manager			−0.011***	
			[−5.073]	
Max Temp 90% (t-2)				0.007**
				[2.041]
Max Temp 90% (t-2) × GUO Manager				−0.022***
				[−6.952]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Precipitation	Yes	Yes	Yes	Yes
Cold days	No	No	Yes	Yes
Observations	2,550,065	2,550,065	2,550,065	2,550,065
R-squared	0.254	0.254	0.254	0.254

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) 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. 'Anomaly1' 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. 'Max Temp 90%' is the percentage of days with daily maximum temperature $>$ 90th percentile of daily maximum temperature centred 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 3 and 4, we also control for cold days effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

see Kalemli-Ozcan et al. 2015). With Orbis data, we can also determine whether each GUO serves as a manager in the firm.

We establish a GUO-Manager dummy to recognise the managerial role of the GUO in the company, and interact it with our weather variables in the baseline model. Tables 18 and 19 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. The absolute effect on the default probability for companies run by the owners is a fall of 10.9 basis points or 5.4% of the average default rate in the sample. For the remaining heat and precipitation measures, we note that the previously observed increase in default probability is absent in firms with a GUO manager.

6. Other robustness

We conduct a series of tests to verify the robustness of our findings. In the primary analysis, we determine the count of relative hot days adhering to the ETCCDI definition. Additionally, for a robustness check, we employ the definitions of relative hot days as proposed by Addoum, Ng, and Ortiz-Bobea (2020), and Cathcart et al. (2025). To calculate this measure, we analyse the distribution of the highest daily temperature for each

Table 19. Impact of precipitation on the default probability when GUO is a manager.

	Default Status			
VARIABLES	1	2	3	4
Av. Daily rain – w/d (t-1)	0.033**			
	[2.349]			
Av. Daily rain – w/d (t-2)	0.035***			
	[2.687]			
Av. Daily rain – w/d (t-1) × GUO Manager	−0.031***			
	[−2.621]			
Av. Daily rain – w/d (t-2) × GUO Manager	−0.038***			
	[−2.684]			
Rainy Days > 1 mm (t-1)		0.001		
		[1.078]		
Rainy Days > 1 mm (t-2)		0.007***		
		[5.244]		
Rainy Days > 1 mm (t-1) × GUO Manager		−0.006***		
		[−3.870]		
Rainy Days > 1 mm (t-2) × GUO Manager		−0.008***		
		[−4.391]		
Rainy Days > 10 mm (t-1)			0.004	
			[1.414]	
Rainy Days > 10 mm (t-2)			0.010***	
			[3.498]	
Rainy Days > 10 mm (t-1) × GUO Manager			−0.012***	
			[−4.372]	
Rainy Days > 10 mm (t-2) × GUO Manager			−0.013***	
			[−3.779]	
Rainy Days > 20 mm (t-1)				0.013***
				[2.771]
Rainy Days > 20 mm (t-2)				0.023***
				[4.662]
Rainy Days > 20 mm (t-1) × GUO Manager				−0.023***
				[−5.231]
Rainy Days > 20 mm (t-2) × GUO Manager				−0.026***
				[−4.278]
Firm FE	Yes	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes	Yes
Temperature	Yes	Yes	Yes	Yes
Observations	2,550,065	2,550,065	2,550,065	2,550,065
R-squared	0.254	0.254	0.254	0.254

Note: This table reports the estimated coefficients for the OLS regression of Equation (1) 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. 'Av. Daily rain – w/d' is the yearly average of daily precipitation on wet days, where wet days are defined as daily precipitation > 1 mm. 'Rainy Days > 1 mm' is the total number of days when daily precipitation > 1 mm in a year. 'Rainy Days > 10 mm' is the total number of days when daily precipitation > 10 mm in a year. 'Rainy Days > 20 mm' is the total number of days when daily precipitation > 20 mm in a year. In each specification, we control for temperature, firm fixed effects, and industry-year fixed effects. T-values based on 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. The coefficients are expressed in percentage terms, meaning they should be multiplied by 100.

specific month/location, utilising historical data spanning from 1974 to 2003. Subsequently, we count the number of days in each month/location during our sampling period (2004–2014) that exceed the 90th percentile of that month's maximum temperature distribution. Ultimately, we aggregate 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 compute the temperature anomaly by subtracting the average yearly mean temperature from 1974 to 2003, a time frame that does not overlap with our estimation period. Unreported results substantiate our primary findings for these two alternative heat measures.

As a robustness test to evaluate whether the impact of temperature and precipitation on default probability persists over a longer horizon, we include three-year lagged weather variables in Tables IA.3 and IA.4. The results confirm the direction and significance of the coefficients for the independent variables as reported in Tables 4 and 5 of the main paper, indicating the robustness of our findings.

While the financially constrained measure developed by Schauer, Elsas, and Breitkopf (2019) is suitable for our study involving European small and micro firms, we lose approximately 2 million observations to compute their financially constrained score. To preserve these observations and circumvent biased measures specific to large firms, we identify firms with higher leverage ratios as financially distressed. As shown 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 rank firms according to their leverage ratio, categorising the top 20% as high-leverage firms. Then, we incorporate the high-leverage dummy into our baseline model, interacting it with the weather variables. Tables IA.5 and IA.6 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.

Lastly, we investigate the possibility of adaptation among Southern European countries. Particularly concerning heat risk, citizens from Southern Europe may acclimatise to hot weather more easily compared to their counterparts from the rest of Europe. Based on this hypothesis, we classify Spain, Italy, and Portugal as Southern countries. The results are presented in Tables IA.7 and IA.8. Regarding heat risk, evidence of adaptation is not observed.[6] Regarding precipitation risk, the Southern countries appear more negatively affected, indicated by a positive interaction term in most instances.

7. Conclusion

Using firm-level default data from six European countries, this paper examines the impact of physical climate risk on the default probability of SMiEs. We document that higher temperatures and more intense precipitation significantly increase default risk. A one standard deviation increase in mean temperature (2.6°C) raises the default probability by 86.5 basis points, while a comparable increase in precipitation intensity raises the default probability by 32.4 basis points. Given projections of substantially larger temperature increases under high-emissions scenarios (ECB 2021), these estimates imply economically meaningful increases in default risk absent effective mitigation and adaptation.

We document substantial heterogeneity in how physical climate risk translates into firm default. Labour productivity losses emerge as a key mechanism, with labour-intensive firms experiencing more than double the default response relative to other firms. Financial constraints further amplify exposure: micro firms and financially constrained firms exhibit significantly higher sensitivity to both temperature and precipitation shocks. Industry characteristics also matter. Firms operating in sectors more exposed to outdoor activities or weather-dependent processes display stronger default responses, whereas some sectors exhibit lower sensitivity. Finally, governance plays an important role: firms in which the ultimate owner is directly involved in management experience a smaller increase in default risk, consistent with stronger incentives to actively manage climate-related disruptions. Taken together, our findings underscore that physical climate risk is unevenly distributed across firms and shaped by size, financial constraints, industry exposure, and governance.

Our results have clear policy implications. SMiES, which play a central role in the European economy, are disproportionately exposed to climate shocks yet typically lack the internal resources needed to adapt. Evidence from the broader literature shows that digital upgrading and organisational flexibility can enhance resilience by reducing operational disruptions and enabling remote or adaptive production models (Browder, Dwyer, and Koch 2024). However, studies also document that limited access to finance and managerial capacity remain key barriers preventing SMiEs from undertaking such adaptations (Herrmann and Guenther 2017; Skouloudis et al. 2020). In addition, supply-chain strategies such as supplier diversification and flexible sourcing have been shown to mitigate localised disruptions from extreme weather events (Ho et al. 2015), reinforcing the importance of policies that lower adjustment costs for smaller firms.

At the macro level, our results highlight the importance of incorporating the physical climate risk exposure of SMiEs into financial stability assessments and supervisory frameworks. Climate stress tests and credit risk models that rely on large listed firms or market-based default proxies are likely to understate vulnerability in regions where small firms dominate economic activity. Public intervention can therefore play a complementary role in enhancing resilience. For example, EU-level disaster relief mechanisms such as the EU Solidarity Fund have provided substantial support to firms in regions affected by extreme weather events (EU Solidarity Fund 2022). Strengthening and better targeting such instruments, alongside improved integration of SMiEs into climate stress-testing frameworks, can help weaken the link between physical climate risk and corporate default, and reduce the amplification of climate shocks through the financial system.

Notes

1. See European Commission's Annual Report on European SMEs 2022/2023
2. Table IA.1 in the Internet Appendix (available upon request) provides an overview of the industrial distribution of firms in our sample, categorised according to the Orbis NACE classification. Sixteen sectors are represented, with Wholesale, Manufacturing, and Construction emerging as the dominant sectors, contributing 29.72%, 19.98%, and 16.11% of observations, respectively, to the overall sample. In contrast, the Mining and Quarrying sector has the least representation, accounting for just 0.39% of the total with only 20,192 observations. However, even within this smallest sector, the number of observations remains large enough to allow us to explore the impacts of climate risk across different industry sectors.
3. Table IA.2 summarises the distribution of firms and firm-year observations by country and firm size. Italy contributes the largest share of firms and observations, and together with France and Spain accounts for more than 80% of the sample. This geographic concentration aligns with evidence that firms most exposed to physical climate risk are predominantly located in Southern Europe (ECB 2021). The table also distinguishes between active, insolvent, and bankrupt firm states based on Orbis classifications. Firms are classified as active when their status is recorded as 'Active,' insolvent when recorded as 'Active default of payment,' 'Active rescue plan,' or 'Active insolvency proceedings,' and bankrupt when recorded as 'Bankruptcy,' 'In liquidation,' 'Dissolved,' 'Dissolved bankruptcy,' or 'Dissolved liquidation.' Because firms may transition across states over time, category shares can sum to more than 100%.
4. Relevant milestones in 2005–2014 include the EU ETS launch (2005) and Phase II (2008), the 2008–2009 Climate and Energy Package, and Renewable Energy Directive 2009/28/EC; internationally, the Cancún Agreements (2010) and Durban Platform (2011) advanced monitoring, reporting and verification and initiated the post-2020 negotiation track. Corporate climate disclosure also expanded rapidly (e.g. CDP responses grew substantially for large, listed firms over 2003–2013). At the same time, early EU ETS phases were characterised by a structural surplus of allowances and extensive free allocation, which severely limited marginal abatement incentives and muted compliance pressure for many covered installations. This is consistent with studies that find little evidence that the ETS materially affected firms' competitiveness in its initial phases (Joltreau and Sommerfeld 2019). To address this, the Market Stability Reserve (MSR) was established in 2015 and became operational post-Paris Agreement in 2019.
5. A 'NUTS region' is a territorial unit defined by the European Union. Each country is divided into three NUTS levels, from major regions (NUTS1) to small regions (NUTS3). In total, our sample comprises 528 NUTS3 regions across six European countries.
6. The Southern adaptation for heat risk is observed in the unreported regression for the number of relatively hot days when firm and macroeconomic control variables are included.

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Data availability statement

The weather data is publicly available. We make use both of the E-OBS daily dataset and E-OBS indices dataset to construct our climate measurements. Navigate to the E-OBS daily dataset via the following link: E-OBS data access (copernicus.eu). In the 'E-OBS datafiles' section, find 'version 23.1e'. Select the row labelled '0.1 deg. regular grid". Under "Ensemble mean':

- Download TG (which corresponds to the file tg_ens_mean_0.1deg_reg_v23.1e.nc).
- Download TN (which corresponds to the file tn_ens_mean_0.1deg_reg_v23.1e.nc).
- Download TX (which corresponds to the file tx_ens_mean_0.1deg_reg_v23.1e.nc).
- Download RR (which corresponds to the file rr_ens_mean_0.1deg_reg_v23.1e.nc).

The above dataset includes daily mean temperature, daily maximum temperature, daily minimum temperature, daily precipitation values. E-OBS also provide climate indices for E-OBS derived using daily minimum temperature (TN), daily maximum temperature (TX), daily precipitation sum (RR). Navigate to E-OBS indices dataset via the following link: E-OBS indices access (copernicus.eu). In the 'Indices files' section, find 'Based on E-OBSv23.1e (up to 31 Dec 2020)', and download the corresponding heat and rain indices.The Orbis data used in this paper is proprietary. To mitigate any survivorship bias, we purchased the data directly from Bureau van Dijk, ensuring that firms which became inactive during the sample period were included. Alternatively, if your institution subscribes to ORBIS for small and micro firms, you can download the financial statements and ownership data directly from ORBIS. However, BVD's AMADEUS or ORBIS products exclude inactive firms after five to ten years, which can introduce significant selection bias.

Disclosure statement

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