The Impact of Global Warming on Small and Micro European firms

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Abstract

With comprehensive financial data from Bureau van Dijk and gridded weather data from E-OBS, we estimate the impact of temperature shocks on small and micro firm performance across Europe. Our study contributes to the limited economic climate literature outside the US market and is the first study to systematically examine climate risk for the small-business sector. We find that mean temperature and extremely hot days have a significant negative impact on firm performance. On average, a firm's operating income decreases by 6.8% when the yearly mean temperature increases by 1°C. Micro and financially constrained firms are more likely to suffer due to rising temperatures. We also document heterogeneous weather effects across different ownership structures and industries.

Keywords: Temperature shocks, small and micro firms, climate risk, firm performance.

1. Introduction

The physical risk events induced by global warming are now more frequent and intense than ever. The dire consequences of climate change are being felt by people and corporations around the world. Wildfires, floods, droughts, and crop failures have all become more frequent and severe. Recent events have provided stark examples of what is expected to become an established trend.[1] Our planet's temperature has so far increased by 0.85°C compared to preindustrial levels (Carleton and Hsiang, 2016). Warming is becoming more rapid, and the global temperature is likely to increase by 1.5°C over the coming decades (IPCC, 2022). Moreover, without actively controlling carbon emissions, it may not be possible to limit global warming to 1.5-2°C, a limit jointly established by 194 countries in the 2015 Paris Agreement.

In this paper, we look at the physical risk of climate change, with particular focus on the impact on the small-business sector of extremely high temperature. The economic importance of weather differences across regions and countries has long been documented in the literature. Dell et al. (2014) show that previous studies have identified a negative relationship between temperature and per capita income, aggregate output, agriculture output, and labour productivity (see also, Gates 1967, Huntington 1924, Montesquieu 1989). More recent studies have taken advantage of the longitudinal data that allows researchers to identify the causal effects of climate change. Hsiang (2010) considers 28 Caribbean-basin countries and finds that national output decreases by 2.5% when temperature increases by 1°C. Dell et al. (2012) find a negative impact of raising temperature on income in poor countries, but little evidence of it in rich countries. Panel estimates for developing countries typically find a negative relationship between bad weather and agricultural output (Lobell et al. 2011, Guiteras 2009,

[1] In 2021, two severe floods hit Europe and China. The European floods affected Germany, Belgium, Romania, and Italy and caused more than 200 deaths and billions of dollars of damage. The Chinese flood was triggered by a record-breaking amount of rainfall in the Henan Province. According to official reports, this flash flood led to $18 billion of damage and 398 deaths (including missing people). In July 2022, UK citizens experienced temperatures of above 40°C for the first time since record began. In the same month, a heatwave in Portugal led to a historical high temperature of 47°C, causing 1,063 deaths between 7 and 18 July.

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

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

We contribute to the literature in the following ways. First, to the best of our knowledge, our paper is the first study to systematically examine the effect of increasing temperatures on the performance of small and micro European enterprises. We use a fine grid of weather data with cells measuring 0.1° latitude by 0.1° longitude. We accurately match firms and weather data by geocoding the postcodes of each firm's registered address and minimising the distances between the locations of the firms' headquarters and the centres of the square cells on the temperature grid. Given the local nature of small and micro firms' operations and the high-resolution E-OBS weather data we employ, our matched firm-specific weather variables are able to reflect precise weather exposure at the firm level. Following the suggestions in the climate economic literature (e.g., Dell et al. 2012, Dell et al. 2014), we run a panel regression model with a battery of fixed effects. To avoid "over-controlling", as suggested by Angrist et al. (2009), we do not include other firm-specific covariates in the regression. Our main finding is that, with a 1°C increase in mean temperature, a firm's operating income decreases by 6.8%. This result is statistically significant at the 1% level.

These results differ from those of Addoum et al. (2020), who study large US corporations. They first match daily temperature data with sales at the establishment level and then investigate how temperature variability affects the firms' sales and profitability. Both the establishment- and firm-level results show that sales, profitability, and productivity are generally unaffected by temperature shocks. By contrast, a later study by the same authors (Addoum et al. 2021) concludes that, in 40% of the US industry sectors they analyse, firms' quarterly earnings exhibit sensitivity to temperature. Investigating worldwide data for medium and large companies, Pankratz et al. (2019) find that extremely high temperatures result in a drop in firms' revenues and operating income. Similarly, Custódio et al. (2022) observe that a 1°C increase in average daily temperature decreases sales to the same customer by 2%. Our focus on small and micro firms complements and extends the above studies. Small companies are more susceptible to adverse weather conditions, as they are often operating with fewer resources, limited access to funding, and geographically concentrated assets. Large firms, in contrast, are more likely to have large inventories, multiple funding sources, and dispersed activities, which may help them to cope with local shocks in temperature and make it more difficult for researchers to establish any causal effect between changes in weather or climate and a firm's productivity.

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

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

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

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

2. Data and Summary Stats

2.1. Sample and Variables

We collect financial and ownership data from Orbis Bureau van Dijk for small and micro firms, from 2005 to 2014. Following the European Commission definition, we define "small firms" as those with a total asset value of between 2 and 10 million Euros and "micro firms" as companies with an asset value of less than 2 million Euros.[2] In our final data, 42.19% of the observations are small firms and 57.81% are micro firms. We remove firms that operate in the public sector or the financial industry, in line with the traditional corporate finance literature.[3] We conduct a set of extensive validation checks of the data and exclude unreliable observations. For example, we filter out records with missing variables and firms for which the location of the headquarter is not given. We also exclude countries with fewer than 900 firm-year observations. Following these checks, we are left with approximately 7 million firm-year observations.

The climate data is collected from E-OBS, which is a daily gridded land-only observational dataset for Europe. Dell et al. (2014) provide a detailed explanation of the types of weather data that should be used for economic analysis. There are four general types: stationary data,

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

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

gridded data, satellite data, and reanalysis data. Gridded data is popular because it uses statistical projections over a grid to increase the data coverage. For example, US weather studies often rely on temperature and precipitation data from the PRISM group, which interpolates weather data at each 4km by 4km cell of the weather grid. Although the E-OBS is generally used to monitor the European climate, it has not been widely used in the finance literature. We collect data on daily mean temperature, daily minimum temperature, daily maximum temperature, and daily precipitation from 1973–2014. The weather data from 1973 to 2003 are used to calculate the historical quantile value of maximum and minimum temperature, while the weather data from 2004 to 2013 are used to match the financial data from 2005 to 2014. We use lagged one-year period weather data for regression analysis.

The E-OBS uses a regular latitude-longitude grid projection, and all weather variables have a resolution at the 0.1° by 0.1° level. The raw database is large, as it includes 14,600 days, and 705 longitude and 465 latitude points. There are approximately 4.8 billion daily weather observations. Since our financial data are annual, we first transform our weather variables of interest from daily to yearly. The mean temperature trend in Europe, using all E-OBS data from 1950 to 2014, is plotted in Figure 1. The fitted trend line reveals a clear upward trend in the yearly mean temperature in the European continent, with an increase of 2.11°C (0.033*64) from 1950 to 2014. This is in agreement with data reported by the European Environment Agency, which shows an average increase of mean near-surface temperature in Europe of between 1.94°C and 1.99°C over the last decade, relative to preindustrial levels.[4] The majority of the change occurs after 1950.

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

- **Mean temp:** the average daily mean temperatures in a year at each location on the weather grid.

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

- **Anomaly:** the difference between the current year's *Mean temp* and the average *Mean temp* computed over the previous 30 years. This measure reflects the deviations of the current *Mean temp* from its past long-run average.
- **Days above 30:** the total number of days above 30°C in a year at each location.
- **Days above 90th**: a relative measure of hot days in a year and a given firm location, taking into account the frequency of abnormally high temperatures recorded in each month at that location. To compute this variable, we consider the maximum daily temperature distribution in any given month/location, derived from historical data for 1974–2003. We then count the number of days in each month/location over the sample period (2004–2014) that have exceeded the 90th percentile of the maximum temperature distribution for that month. Finally, we add together all the days that exceeded the 90th percentile across all the months in the year of interest for each firm location.
- **Days above 90th & 30**: the number of days on which the daily *maximum* temperature was above the 90th percentile of the daily *maximum* temperatures and above 30°C.

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

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

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

2.2. *Summary Statistics*

Table 1 reports the sample distribution across the European continent. Our sample include Europe's largest national economies, such as Germany, France, the United Kingdom, Italy, Spain, and the Netherlands. As both southern and northern Europe countries are represented, we are able to consider a wide range of weather conditions and fluctuations over time. Italy and France together contribute almost half of the firm-year observations, with 25.07% and 25.13%, respectively. Switzerland has the smallest number of observations (998).

Table 2 presents the distribution of industries in our sample, following the Orbis NACE classification. The wholesale, manufacturing, and construction industries have the largest numbers of firms, accounting for 30.08%, 18.91%, and 15.25% of the total firm-year observations, respectively.

Table 3 summarises the firm-level financial ratios. All the variables are winsorised at the 1% and 99% levels. As we can see, the mean values of operating income and EBITDA are 5.8% and 9.5%, respectively. The average log value of the total assets of the firms in our sample is 7.29, which equates to approximately 1.5 million Euros. The average firm age is 16.8 years.

To illustrate the global warming trend in Europe, Table 4 shows temperature anomalies over time. Temperature anomalies tell us by how much the mean temperature in a year deviates from its past long-run value. Table 4 illustrates that, in 8 of the 10 years in the sample period, temperatures were abnormally warm. For example, the weather anomaly in 2011 was 0.85°C higher than in the previous 30 years. Figure 2 shows a temperature-anomaly heat map, year by year across the European continent, using raw weather data from E-OBS. The majority of the European continent is coloured red in each year, meaning that the global warming trend holds not only at the aggregate level but also in most locations across Europe.

Table 5 presents the summary statistics of our temperature variables. The average yearly mean temperature in our sample is 12.52°C, and the standard deviation is 3.48°C.

In Europe, there are 28 days above 30°C and 48 days below 0°C in an average year. Assuming the weather distribution at each location never changes over time, there should be 36.5 days above the 90th or below the 10th percentiles, with 18.25 days above the 95th or below the 5th percentiles. In reality, we observe more extreme hot days (54.15 at the 95th percentile and 31.09 at the 90th percentile) and fewer extreme cold days (29.77 at the 5th percentile and 15.05 at the 10th percentile) than expected, both of which clearly point to global warming.

Table 6 shows the mean values of various temperature measures for different countries. We see that Spain has the highest mean temperature (15.72°C) and largest number of days above 30°C in a year (54.01). Finland has the lowest mean temperature (5.18°C), while Denmark has the smallest number of days above 30°C in a year (0.37). It is worth noting that the above statistics describe temperatures at the locations of the firms in our sample. This means that they indicate average conditions in the most densely populated areas and not necessarily the average temperatures across the countries' respective territories.

3. Methodology

To test the relationship between the firms' profitability and temperature shocks, we run regressions of firm-level profitability on various temperature-exposure proxies. Firm profitability is measured as operating income over total assets. We follow Dell et al. (2012) and Dell et al. (2014) and use panel regression as our baseline model. Standard errors are two-way clustered at the firm level and country-year level (Baum et al. 2011), as they are more robust than single clustering in this setting (Addoum et al. 2020), and two-way clustered standard errors are more robust than standard errors clustered at the firm level or adjusted for spatial correlations in this setting. The model is as follows:

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

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

It is difficult to tell which firm-specific controls, such as accounting ratios, would be affected by temperature exposure. If they are affected, their inclusion in the regression alongside our temperature variables would prevent us from measuring the true impact of temperature on the firm's profitability. In this case, firm-specific covariates could be "bad controls", as observed by Angrist and Pischke (2009). For this reason, we do not employ firm-level time-varying controls in our regressions, in line with Addoum et al. (2019). We control for precipitation, as the profitability of some industry sectors can be influenced by both temperature and rainfall (e.g., the agriculture and water utility sectors). We lag our weather variables to ensure that there are no lead effects due to the different reporting dates of the firms in our sample. For example, for many firms, the reporting date is 31 March. In that case, it would be inappropriate to use average weather temperatures over that year. As a robustness check, we also estimate panel regression with contemporaneous weather variables, and the results hold.

4. Results

4.1. Baseline Estimates

Table 7 presents the results of the baseline regression. We find that temperature exposure has a significant impact on operating income in all seven specifications shown in the table. Model 1 shows the estimate for *Mean temp* and indicates that a 1°C mean temperature increase will lead to a highly statistically significant 0.393% drop in the ratio of operating income to total assets, representing a decline of 6.8% relative to the ratio's mean value (5.8%)

reported in Table 3. This is an economically significant loss for a firm. In model 3, we investigate the impact of the number of hot days above 30°C. On average, *Operating income* will fall by 5.3%, relative to its mean value, for a one standard deviation (28.08 days) increase in hot days above 30°C. However, this result is only statistically significant at the 10% level.

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

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

Overall, our findings on the negative effects of hot weather are in line with those in the existing literature (e.g., Addoum et al. 2021, Pankratz et al. 2019, Pankratz and Schiller 2021, Custódio et al. 2022). Pankratz et al. (2019) find that an additional hot day decrease quarterly operating income to total assets by 0.003%, which is comparable to our finding of an annual operating income ratio falling by 0.011% (close to the compounded value of 0.003% over four quarters).

4.2. Financial Constraints

In comparison with large corporations, small firms may be less able to face extreme weather due to their reduced ability to redistribute resources away from the affected areas

(Custódio et al. 2022). If size is a determining factor of weather vulnerability, we should observe a differential impact of temperature exposure between small firms and micro firms, with the latter being more affected. We proceed with our analysis by extending our baseline models, interacting the temperature-exposure variables with a firm-size dummy to identify the micro firms. The results are reported in Table 8. We find a statistically significantly negative impact for all interacted terms across all regression specifications. The mean temperature data reveal that micro firms' operating income shrinks by 35.10% more than that of small firms (0.119%/0.339%). In relation to absolute and relative hot days, we observe that small businesses are not significantly affected. This suggests that the negative and mildly statistically significant effects observed in Table 7 for the whole sample is due to the negative influence of temperate exposure on micro firms' profitability. Indeed, the coefficients of the temperature variables interacted with the micro dummy in Table 8 are highly statistically significant and 2–3.5 times larger than the coefficients of the hot day variables in Table 7.

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

The results reported in Table 9 show that, in all the regression specifications, a statistically significant negative effect is found for the interaction term of the financial-constraint dummy and for each of the temperature-exposure measures. Regarding the mean temperature, both baseline and interaction terms have statistically significant negative coefficients. Compared with unconstrained firms, financial constrained ones suffer an additional 65.5% (0.163%/0.249%) contraction in operating income in warmer weather. Looking at the extreme hot days measures, we find only the interaction term to be statistically significant, which suggests that only financially constrained firms have suffered due to absolute or relative hot days. The fall in average operating income triggered by a one standard deviation change in hot day measures varies between 12% and 18%, depending on the measure.

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

4.3. Owner-Manager

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

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

Table 10 reports results for the baseline model augmented with ownership type dummies interacted with temperature-exposure variables. We find that, for firms controlled by families or the government, the negative impact on profitability of increases in mean temperature are partially (families) or fully (government) neutralised. Indeed, for government owners, the overall impact is positive. For industrial and financial owners, the coefficient of the interaction term is not significant, which implies that firms in this category suffer a reduction in operating income with warmer climate, in line with the baseline findings. Our results are in line with Gentry et al. (2016), who document the long-term orientation and higher risk aversion of family-owned businesses. We conjecture that this could lead to greater efforts to mitigate climate-change risk, which would make family-owned firm more resilient to higher temperatures. Similarly, as government-controlled firms are known to be more risk averse than other types of firm (Boubakri et al. 2013), it is not surprising to see that they are better able to face the effects of climate change and hence show greater endurance to a warmer environment. Table 10 shows some evidence that family- and government-owned firms are also less vulnerable to relative hot days. The same result is not observed for absolute hot days.

We further investigate whether the impact of weather conditions on a firm’s performance could be influenced by the extent of the “agency problem” between owners and the firm management. When owners are also managers, they have an increased exposure to firm-specific risk because they have invested both their wealth and their own human capital in the firm. This is likely to decrease their risk tolerance (Brisley et al 2021) which, as for family-owned companies, may generate incentives to mitigate climate risk. Our findings in Table 11 support this conclusion. In the table, we use the baseline model with temperature variables interacted with a dummy which identifies whether the GUO is a current manager. In our sample, -35.82% of the GUOs are also current managers of the firms. As shown in the Table, the negative impact of mean temperature on profitability is significantly reduced if the GUO is also a current manager.

4.4. Industry Effects

Weather's heterogeneous impact across industries has been documented in several studies. Addoum et al. (2021) show that over 40% of US industries are significantly affected, positively or negatively, by temperature shocks. Industry-related sensitivity to heat is also found by Pankratz et al. (2019), Custódio et al. (2022), and Graff Zivin and Neidell (2014).

Arising from this is the question of whether the heterogeneous industry effects observed in large firms can also be observed in small businesses. We analysed the industries represented in our sample individually and, as in previous literature, found heat sensitivities. In Tables 12 and 13, we illustrate two such cases in which industry-specific dummies interacted with temperature variables and show statistically significant coefficients. In Table 12, we look at the energy and utilities sectors. Here, the interaction term has a significantly positive effect for both mean temperature and the relative hot days measure. The interaction coefficient is larger than that of the reference base group, which indicates that warmer weather does not cause these sectors to become less profitable. This may be because the more extreme weather conditions caused by global warming require more energy for both cooling and heating systems in private and commercial properties. Indeed, a recent article in *Science* (Cohen et al. 2021) argues that warming in the Arctic can be linked to extreme cold weather in parts of North America and Asia.

We test the agriculture industry separately. Table 13 shows that hot days, both absolute and relative, can produce a positive and statistically significant impact on the profitability of agricultural firms. However, the interaction of the agriculture sector dummy and mean temperature is not significant. This ambiguity in our findings is not surprising. As noted by Kim (2012), the effect of global warming on agriculture can be positive or negative, depending on a number of factors. A warmer climate and higher levels of carbon dioxide in the atmosphere can increase crop yields as the cultivation period expands and CO_2 acts as a fertiliser. Higher temperatures can also reduce the damage done by low temperatures to winter crops. By contrast, extremely high temperatures can reduce the quantity and quality of crops (partly due to an increase in weeds and pests) and reduce land fertility due to soil erosion caused by heavy rains and floods. Some areas may be disadvantaged by extreme heat, while others closer to the pole or at higher altitudes may benefit from warmer weather.

5. Robustness

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

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

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

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

6. Conclusion

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

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

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

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

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

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

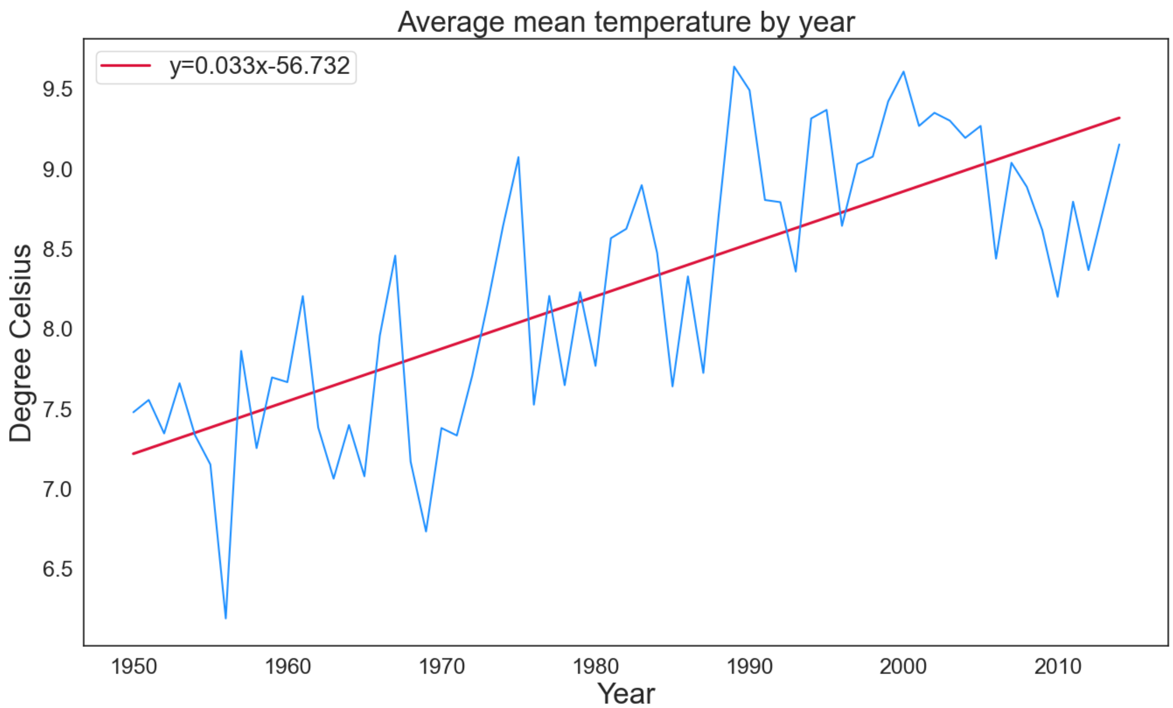

Fig. 2. Temperature anomaly in Europe by year, 2004–2014

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

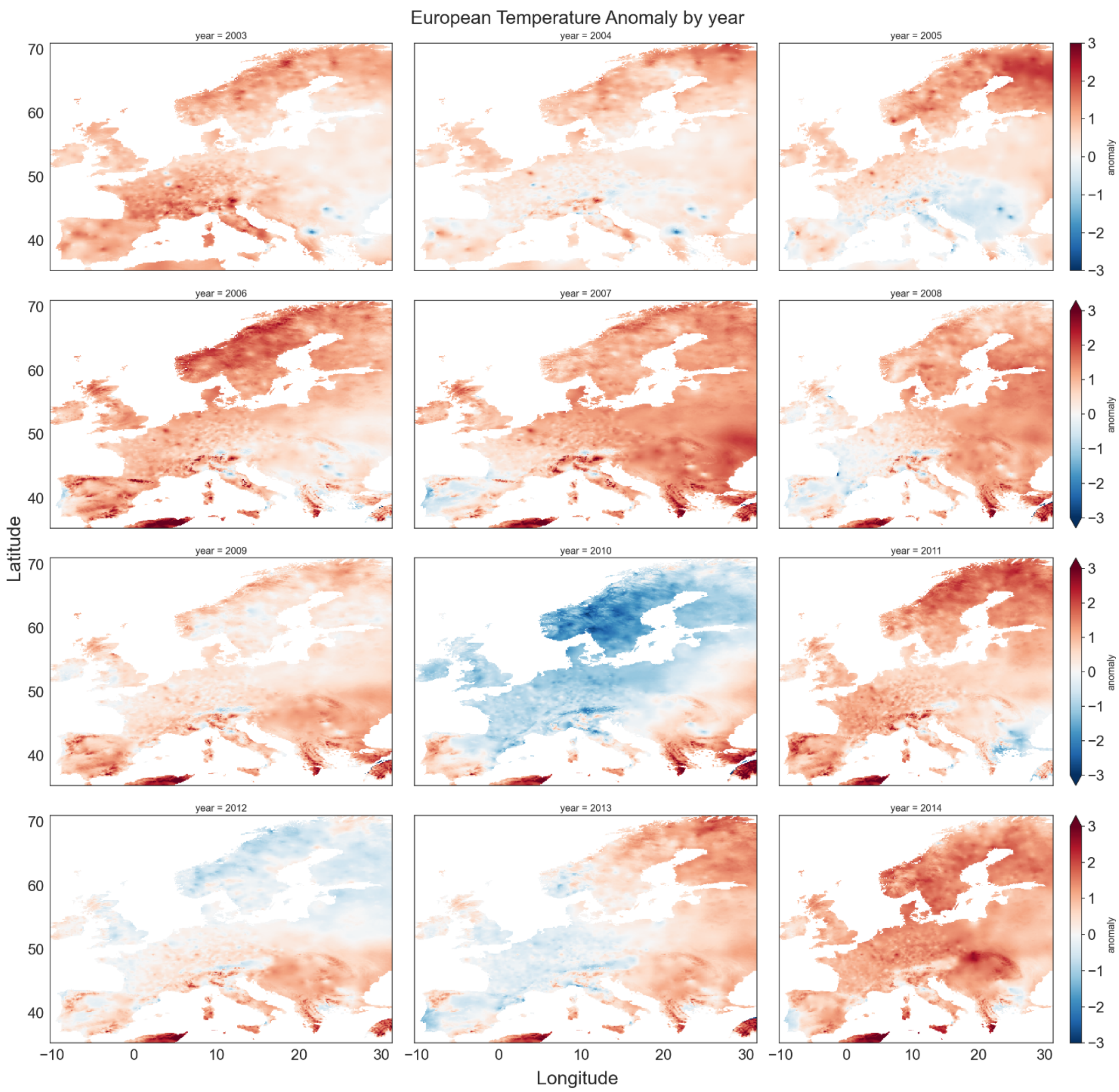

Table 1: Country distribution

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

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

Table 2: Industry distribution

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

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

Table 3: Summary statistics of accounting ratios

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

Variables	**Mean**	**SD**	**p25**	**p50**	**p75**
Operating income	0.058	0.149	0.008	0.047	0.112
EBITDA	0.095	0.152	0.029	0.081	0.158
Net income	0.034	0.124	0.000	0.023	0.079
Size	7.292	1.075	6.570	7.361	8.110
Age	16.812	13.507	6.844	13.849	22.858
Cash holding	0.149	0.180	0.016	0.075	0.219
Interest coverage	27.016	101.873	0.886	3.267	14.647
Financial constraint (FCP)	-1.911	2.792	-1.948	-1.275	-0.998
Financial constraint (SA)	-3.711	0.599	-4.001	-3.614	-3.309

Table 4: Temperature anomaly by year

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

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

Table 5: Summary statistics of temperature exposures

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

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

Table 6: Temperature by country

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

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

Table 7: The impact of temperature on firm profitability

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

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

Table 8: The impact of temperature on the profitability of micro firms

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

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

Table 9: Firm profitability, temperature, and financial constraints

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

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

Table 10: Ownership structure

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

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

Table 11: Manager-owner

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

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

Table 12: Energy and utility sectors

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

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

Table 13: The Agriculture Sector

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

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

Appendix

A.1: Financial constraints in small firms

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

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

A.2: Financial constraints in micro firms

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

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

A.3: Financial constraints – alternative constraint indicator

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

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

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

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

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

A.5: Financial constraints in micro firms – alternative constraint indicator

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

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