The Effects of Extreme High Temperature Spells on Financial Performance

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Abstract. We examine EU and UK firms to investigate the impact of spells of extreme high temperature on three common financial performance measures: the ratio of sales-to-assets, pretax profit margin, and return on assets. Supporting our hypotheses, we find that spells of extreme high temperature have a curvilinear impact on financial performance. While extreme high temperature spells tend to degrade financial performance in regions or months with normally hotter conditions, the opposite effect is observed for extreme high temperature spells in regions or months with normally cooler conditions. Given our environmental context, where the standard temperature is about 16˚C, high temperature spells with maximums that well exceed that temperature have marked financial implications. We also find that spells in locations with maximum temperatures above 23˚C associate with smaller improvements in ESG scores and higher carbon emissions in the future, suggesting that managers' actions to mitigate the risks of high temperature spells are limited at best. Our evidence of significant impacts of extreme temperature on firm performance but little action in response supports the view that managers need more guidance on how to measure the risks and opportunities of extreme weather events and the policies to manage them.

Keywords. Extreme high temperature spells; response of financial performance to extreme high temperature; curvilinear impact; ESG performance; carbon emissions

JEL Classification. G14; Q51; Q54

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1. Introduction

Short spells of extreme high temperature, which have grown more frequent and severe, pose a significant hazard to human health, causing death among the most vulnerable in many regions of the world (Liu et al. 2022). Of the many kinds of extreme weather, spells of extreme high temperature stand out as the most devastating (IFRC 2022). While many settings document the human and environmental effects of extreme high temperature (e.g., Barreca 2012; Dahl et al. 2019; Hoeppe 2016; Otto et al. 2018; Zanocco et al. 2018), less well documented is how short spells of extreme high temperature affect firms' financial performance, especially whether these effects follow a nonlinear pattern, implying that financial performance could improve for extreme high temperature spells in regions with normally cooler conditions, yet degrade in areas that are normally hotter. These impacts on financial performance–increasingly linked to a changing climate–may also require actions by firms to mitigate the threats or exploit the opportunities from higher temperatures. This is due to an emerging consensus that a firm's capacity to manage emissions to achieve net-zero targets and the outcomes of extreme temperature are intricately connected. A deeper understanding is required. There is also a pressing need to document the extreme temperature-financial performance link to improve the science of disclosure around weather events such as spells of extreme high temperature. The Task Force on Climate-related Disclosure (TFCD 2017), already a key building block for standards in Europe (CSRD 2021; ISSB S1 2023; ISSB S2 2023) and elsewhere (SB-253 2023; SEC 2024), specifically advocates for the disclosure of climate-related impacts, singling out extreme weather as an acute event-driven risk. Brooks and Schopohl (2021) emphasize the need for academics to study how extreme weather shapes firms' environmental disclosure practices.

In this study, we examine two primary questions. We first investigate whether and how spells of extreme high temperature impact financial performance and whether these impacts vary systematically on the firm-level, locational, temporal, and sectoral characteristics of such spells. We then explore as our second question whether and how extreme high temperature spells relate to firms' future environmental, social, and governance (ESG) performance and emission levels, as a way to reveal proximately whether temperature-affected firms take actions to streamline their operations for ESG performance or reduce their emissions to mitigate or counterbalance these effects. In short, our goal is to initially identify the financial effects of extreme high temperature spells and then investigate whether they plausibly relate to firms' actions to address temperature threats in the future.

Our research questions require study for several reasons. First, despite an extensive literature on extreme temperature's human and environmental toll, only a few studies examine how extreme temperature spells impact financial statements at the firm level (Addoum et al. 2020; Addoum et al. 2023; Jin et al. 2021; Pankratz et al. 2023). More evidence is required to establish a consensus. Second, central banks, including members of the Network for Greening the Financial System (NGFS 2019), the European Parliament (EU 2022), and global alliances (e.g., the G7, European Green Deal (EU 2023), BIS (2021)) have all identified extreme weather as critical to how climate change shapes economic growth and stability. Our study is, thus, relevant from a prudential standpoint. Third, the potential and actual effects of extreme weather on firms' operations, infrastructure, and productivity (Atlantic Council 2021; Coonan 2023) underscore the need for further study of firms' responses to extreme weather, including managers' actions to mitigate or adapt to such risks and enhance corporate disclosure for the benefit of stakeholders. Firms worldwide still disclose little in their financial or sustainability reports on the risks and opportunities of extreme weather despite regulatory attention to increased disclosure (CSRD 2021; ISSB S1 2023; ISSB S2 2023; SEC 2024)[1], arguably belying the view that extreme temperature threats are real. We are not aware of prior studies

[1] The SEC final rule on mandatory climate change disclosure (SEC 2024) includes 33 mentions of "temperature" in combination with qualifiers such as "extreme", "increase", "rise", "higher", or "global", and "heatwave" or "heat stress".

of firms' actions to adapt to or mitigate the impacts of extreme temperature events on financial performance, so our second question is new.

As context, we study a large sample of mostly private firms in the European Union and the United Kingdom. Several factors motivate this choice. First, the firms in our study period of 2011–2019 operate under mostly common country-level rules and legislation (i.e., those established by the European Parliament) relating to the environment and climate change. Second, the firms reside in countries reflecting wide variation in geography and temperature (DeGuindos 2021). Third, private firms often exhibit less diversification than public firms, rendering them more prone to local weather.

To provide the largest possible sample of EU and UK firms, we require each firm in the BVD Orbis dataset to have data to enable the calculation of the ratios of annual sales-to-assets and net profit-to-sales and the book value of equity. This yields a sample size of a maximum of 559,077 firm-year observations (499,760 private firm and 59,317 public firm observations) for 57,672 EU and UK firms from 2011 to 2019. We next extract from Copernicus data on the timing, length, location, and critical temperature levels experienced during every extreme temperature spell in the countries where the firms are located. Guided by the definitions of the US National Weather Service, the EPA, and NASA,[2] we define an extreme temperature spell as occurring when the daily temperature exceeds the 95th percentile of the daily temperature recorded at the same location in the same season over the past five years for at least two consecutive days (details in Section 3) (We repeat our tests for three-day spells.) We then match each extreme temperature spell to the firms in our sample based on headquarters location. We source the location of each firm's headquarters from Eikon Datastream. These steps expose our sample of public and private firms to a total of 2,274,518 day-specific spells of extreme temperature.

[2] NOAA. https://www.weather.gov/safety/heat-during; US EPA. https://www.epa.gov/climate-indicators/climate-change-indicators-heatwaves#tab-5; NASA. https://www.earthdata.nasa.gov/topics/atmosphere/weather-events/heatwave.

To relate the accounting ratios to the 2.27 million day-specific extreme temperature spells, we combine the spell characteristics of each firm in a year. To assign a temperature measure to an extreme high temperature spell, we calculate the average of the maximum temperature within each spell experienced by a firm in a given year (Russo et al. 2014). In the empirical analysis, we denote this measure as *SPELL_MAX_TEMP*. For duration, we sum the number of days of the extreme temperature spells experienced by a firm for each firm-year. In the empirical analysis, we denote this as *DURATION.* For some tests, we average the extreme high temperature spells over a season within a year.

We next use regression analysis to relate financial performance to the firm-level measures of extreme high temperature spell. Building on the literature on how and why extreme temperature affects employee productivity, sales effort, and consumer demand (Section 2), we posit that extreme temperature spells have a nonlinear (more specifically, a curvilinear) effect on financial performance.[3] On the one hand, a firm could experience an extreme high temperature spell in a location of normally cooler temperatures (e.g., Sweden). This could stimulate employee effort and consumer demand and would represent a positive response of financial performance to extreme temperature. On the other hand, a firm could experience an extreme high temperature spell in a location of normally hotter temperatures (e.g., Spain). This could dampen sales effort and customer demand because it may simply be too hot for an employee to work effectively or a consumer to engage in purchasing products or services. This would represent a negative response of financial performance to extreme temperature. Thus, over the range of low to high extreme temperature spells, we expect that financial performance will increase at a decreasing rate for low extreme temperature spells and then decrease at an increasing rate for high extreme temperature spells. In the paper, we refer to this curvilinear

[3] Strictly speaking, our main model (Section 4) to explain financial performance is curvilinear rather than nonlinear because it is linear in spell temperature and the square of spell temperature. This makes it a polynomial function of order two. However, because the financial performance-to-extreme temperature response function is hump shaped and not a straight line, the text also refers to the shape of the function as nonlinear.

response as a hump shape, where the maximum temperature at the top of the hump is the inflection point.

We then investigate how the hump shape varies on firm-level, locational, temporal, and sectoral characteristics. For example, sales effort and demand may increase in response to an extreme temperature level above a critical level for firms in the energy sector. Also, firms in high latitudes, which have normally cooler temperatures, may be less likely to experience temperature extremes, even in periods of normally hotter temperatures, such that sales may not decline during spells of extreme high temperature.

We document four sets of findings. We first establish that extreme temperature spells impact the sales-to-assets ratio as a hump-shaped relation. This means for spells above a critical temperature, the relation between the sales-to-assets ratio and firms' exposure to extreme high temperature shifts from positive to negative. Empirically, the sample-wide critical temperature (i.e., the inflection point of the curve) occurs at 22.95˚C (hereafter rounded to 23˚C). This result is also supported in studies unrelated to financial performance (Section 2). To assess economic significance, we measure the impact on the sales-to-assets ratio of one or more additional degrees of Celsius above the inflection point. For our full sample of firms in the UK and EU, if the maximum spell temperature were to exceed the sample-wide average of 23˚C by 5˚C, the sales-to-assets ratio of the average sample firm would drop by 2.0 percent.[4]

Second, we find a mostly hump-shaped relation between pre-tax profit margin and extreme temperature spells. That is, while the sales-to-assets ratio increases and then decreases over the range of maximum spell temperatures, the increase in expenses during lower extreme temperature spells is more than enough to offset the increase in sales to generate an increase in pretax profit margin. By contrast, for higher extreme temperature spells, pretax profit margin decreases because sales are lower with no corresponding decrease in expenses. In terms of

[4] This 2% drop in the sales-to-asset ratio in response to spells of extreme temperature above 23˚C is based on the full sample and represents an average effect. Table 3 shows that the responses vary by the time and place of a weather condition. Fig. 2.2 shows that the 23˚C inflection point also varies by time and place.

economic significance, if the maximum spell temperature were to exceed the sample-wide average of 23˚C by 5˚C, the sample-wide pretax profit margin would decrease by 1.4 percentage points (from 11.2 percent of sales to 9.8 percent of sales), or a drop of 12.9 percent.

Third, we combine the sales-to-assets and the pretax margin ratios to estimate the effect of extreme temperature spells on pretax return on assets (ROA). We find that the response of ROA to extreme high temperature spells is mostly increasingly negative over the range of maximum spell temperatures. In economic terms, if the maximum spell temperature were to exceed 23˚C by 5˚C, the sample-wide pretax ROA would decrease by 7.7 percent when the spell lengths for the average sample firm sum to 15 days per year.

Fourth, we explore whether extreme high temperature spells associate with changes in firms' future ESG performance and emission levels. We find that extreme high temperature spells do not associate with improved ESG scores or lower emissions in the future, which they should if these measures were to reflect managers' actions to have invested in infrastructure to lower the risks of future extreme temperature spells on operations. This suggests that firms' present actions are insufficient to mitigate the risks of extreme high temperature spells. A plausible explanation for this putative managerial passivity could be a lack of awareness of the effects of extreme high temperature spells on performance as documented in this paper.

We run a multitude of sensitivity tests. These tests show that our results are robust to alternative designs and additional covariates and support predictions for subsamples. Our findings strengthen for firms with fewer subsidiaries. These are firms whose headquarters location is likelier to coincide with the location of their customers and operations. Our findings strengthen for firms located more than 100 km from the closest EU or UK capital city. These are firms in regions less resilient to the infrastructure of a major city that can attenuate extreme high temperature spell impacts on employees and consumers. We show that endogeneity from potentially omitted covariates is not a concern and that placebo tests designed to refute the underlying logic of the study's design do not support our main inferences.

As a main contribution to the literature, our paper establishes a robust hump-shaped relation between extreme high temperature spells and key indicators of firm-level financial performance. We also show that the key indicators vary predictably across firms, locations, and sectors. This evidence effectively rebuts the notion that extreme weather holds little financial significance for investors, a finding reported in earlier work (Addoum et al. 2023). The documented hump shape between extreme high temperature spells and financial performance also differs from earlier work that finds either no response in financial performance (Addoum et al. 2020; Jin et al. 2021) or one that is uniformly negative and linear (Pankratz et al. 2023). Yet, at the same time, we are unable to document that firms take actions within three years of the weather events to mitigate the arguably higher risks to their infrastructure and operations. Rather, we find that the hump-shaped relation between financial performance and extreme high temperature spells does not moderate over time, and when the high temperature spells occur in normally hot months or locations, firms' ESG scores trend lower and emissions trend higher in the next three years. These trends align more closely with a business-as-usual stance. That extreme high temperature can affect financial performance negatively and that firms appear to lack a corrective response together provide strong motivation for enhanced non-financial disclosure. With enhanced non-financial disclosure, investors would become more aware of the risks of extreme high temperature spells and how firms manage that risk and, thus, abler to price securities more efficiently (Pedersen et al. 2021).

In keeping with this view, the Task Force on Climate-Related Financial Disclosure (TFCD 2017), the Securities and Exchange Commission (SEC 2024), and others (ISSB S1 2023; ISSB S2 2023) have singled out extreme weather as an acute financial risk requiring disclosure and audit if material. The equations in our paper could serve as a useful tool for managers to assess the impact of an extreme temperature spell on future firm performance. The likely costs of spells of extreme high temperature for businesses can be substantial (Coonan 2023; ILO 2019). These assessments may not occur, however, if managers attach a low priority to the extreme weather phenomenon or do not have the expertise to ascertain and quantify its repercussions.

2. Literature and Hypotheses

2.1 Financial performance and extreme temperature

The literature on financial performance and extreme temperature is sparse and mixed.[5] While the few studies so far (Addoum et al. 2020; Addoum et al. 2023; Jin et al. 2021; Pankratz et al. 2023) mostly predict that extreme temperature could impact financial performance adversely, with exceptions for firms that adopt mitigation policies as countermeasures and utilities and energy firms that may benefit because the demand for their products or services can increase, their results do not always support their predictions. Addoum et al. (2020) find no evidence of a link between the number of days of anomalous (extreme) temperature and local sales. Jin et al. (2021) report a similar result. Extending their study, Addoum et al. (2023) find no evidence that analysts or investors react promptly to anomalous temperature events. By contrast, Pankratz et al. (2023) find that the ratios of sales-to-assets and operating income-to-assets decrease linearly in the number of extreme temperature days. These studies, thus, report divergent findings. Yet, they share common definitions of anomalous temperature (based on the number of anomalous temperature days) and aggregate daily temperature extremes in similar ways to match to the financial data. Their emphasis, though, is on the number of anomalous temperature days rather than the intensity of the temperature itself within a spell of extreme temperature, which is the focus here.

Consistent with established climate studies (e.g., Zivin and Neidell 2014), we posit that the effect of an extreme temperature spell on financial performance arises mainly through the *level* of its temperature (an intensity dimension) and that the number of days of high

[5] For example, no mention is made of the role of the effects of extreme weather in a review of 1,141 papers and 27 meta-studies published between 2015 and 2020 on the link between ESG and financial performance (Whelan et al. 2021), despite the view that weather can impact ESG as an "E", "S", or "G" issue and, thus, should be paramount in understanding the role of ESG for financial performance.

temperature (a duration dimension) is secondary to this effect. That is, the main catalyst for lower sales or workplace productivity–whether from degraded infrastructure, physical prevention, or biological and physiological factors–is the intensity of an extreme temperature spell relative to a norm rather than how many days the spell lasts. The average duration of an extreme temperature spell is also quite short (e.g., 3 to 4 days in general[6] and 3.88 days for our sample). Herein lies a pivotal aspect of our study. Rather than emphasizing the number of days of extreme temperature (or "time exposure" as per Addoum et al. (2020)), our key explanatory variable is the maximum temperature within an extreme temperature spell, which we posit affects financial performance differently depending on whether the extreme temperature spell occurs when the normal weather at the time is cooler or hotter. That is, for extreme temperature spells in normally cooler conditions, financial performance should respond positively to extreme temperature spells, whereas in normally hotter conditions financial performance should respond negatively.

Evidence from several literatures supports our expectation of a curvilinear or hump-shaped response. One literature relies on predictions from physiology and biology, wherein outdoor temperature extremes affect employee and customer decision-making through variation in emotive factors such as apathy, mood, sentiment, and stress. Consistent with a nonlinear relation, Baylis (2020) finds that outside maximum temperature affects Twitter sentiment nonlinearly as a hump-shape, peaking at approximately 21˚C.[7] The trigger for lower sales or employee productivity has also been linked to weather-induced degradation in infrastructure (Swerling and Murphy 2022) and physical prevention (Agnew and Thornes 1995).[8] The International Labor Organization predicts that more than two percent of working hours will be

[6] https://www.epa.gov/climate-indicators/climate-change-indicators-heat-waves.
[7] The hump shapes reported in Baylis (2020) of the response of Twitter sentiment to temperature are also "markedly similar across the choice of measure of sentiment and both qualitatively and quantitatively consistent across a range of different specification choices." (p. 2).
[8] Outdoor temperatures may also exceed "official" outdoor temperature readings in smaller spatial resolution grids due to the density of city buildings, which can create additional heat from cooling systems (Luo et al. 2020).

lost to rising temperatures by 2030 (ILO 2019). Behavioral finance papers also link weather to market activity (Cao and Wei 2005; Floros 2011; Hirshleifer and Shumway 2003). A second literature links variation in financial performance to indoor temperature through workplace productivity (Zivin and Neidell 2014; Kekäläinen et al. 2010; Seppanen et al. 2006; Zhang and Shindell 2021; Zhao et al. 2021). So, it is not just outdoor temperature that may explain our findings. Seppanen et al. (2006) document that an indoor temperature of 21.75˚C associates with the highest worker productivity, which then decreases by nine percent when it reaches 30˚C. Third, the marketing literature on extreme weather and consumer demand supports a curvilinear relation (Badorf and Hoberg 2020; Zwebner et al. 2014). Zwebner et al. (2014) show that temperature extremes relate to customers' intention to purchase. Fourth, the climate literature in general supports a curvilinear relation (Burke et al. 2015; Zivin and Neidell 2014; Schlenker and Roberts 2009). It is challenging, though, to tie together the threads in these literatures to link extreme temperature to economic decision making and financial performance on a common dimension. Rather than pinpoint a single channel or mechanism to explain our predictions, we view our findings as multidimensional in the many factors identified in the literature. Based on these factors, we posit a hump-shaped curvilinear relation between financial performance and extreme weather, such that at some point (the inflection point of the curve) the response of financial performance to extreme temperature spells shifts from positive to negative.

Specifically, we expect extreme high temperature spells to have positive (negative) effects on financial performance below (above) a critical level that exceeds the 95th historical percentile versus not exceeding the historical benchmark. We state these expectations below.

H1. Financial performance relates negatively (positively) to extreme high temperature spells above (below) a critical temperature level as a hump-shaped curvilinear relation.

H2. The inflection point on the hump-shaped curvilinear relation between financial performance and extreme high temperature spells occurs when the maximum spell temperature reaches a critical level.

Because some prior research focuses on extreme temperature days, we investigate the role of spell duration. If extreme temperature spells with maximum temperatures above (below) a critical level decrease (increase) financial performance on average (*H1* and *H2*), then longer extreme temperature spells with critically high temperatures should decrease (increase) financial performance even more. We first test whether financial performance relates negatively (positively) to the duration of an extreme temperature spell as a response incremental to the effect of temperature level. This is a direct effect. However, if duration has an offsetting effect depending on whether the extreme temperature spell occurs in normally warmer or cooler conditions, we may not find an overall effect. We therefore test whether the impact of extreme temperature spells on financial performance (*H1* and *H2*) intensifies for shorter or longer duration extreme temperature spells. This is a conditional effect arising from the interaction of temperature and duration. Accordingly, we state this expectation as H3.

> H3. Longer (shorter) extreme high temperature spells intensify (weaken) the hump-shaped curvilinear response of financial performance to extreme temperature spells.

We also explore whether the hump shape and the inflection point of the curve vary systematically by a firm characteristic such as sector, location, season, the number of subsidiaries, and the vulnerability of the country of a firm's location to climate change. Firms' financial performance in a particular location (e.g., normally cool, high latitude locations) or sector (e.g., energy) may not decline during extreme temperature spells with temperatures that exceed the norm for that situation. We also investigate whether the impact of extreme temperature might have attenuated over time. This builds on the idea that as extreme temperature spells become more frequent and severe (IFRC 2022; IPCC 2021), firms develop strategies to exploit or alleviate their impacts.

3. Data and Sample

3.1 Temperature data

We define an extreme temperature spell as one when the Copernicus ERA5 Near-Surface Air Temperature (NSAT) exceeds the 95th percentile of the daily temperature recordings at the same Copernicus grid location (based on latitude and longitude) in the same season over the past five years for at least two consecutive days. We also examine samples of three-day and longer extreme temperature spells. We extract these data using a latitude-longitude grid with a $0.25^\circ \times 0.25^\circ$ spatial resolution (Collins et al. 2013), which is common to the literature (Zhang and Shindell 2021).[9] We assign every firm-year to a tile in the NSAT grid. We calculate the duration of an extreme temperature spell as the number of consecutive days a firm is exposed to a temperature exceeding the five-year trailing 95th percentile of daily temperatures in the same season.[10]

Fig. 1 plots the distribution of the Copernicus extreme temperature spells in the EU and the UK for the astronomical summer months of July, August, and September in 2011–2019. The light grey surrounds in the figure represent a *NUTS2* territorial division.[11] The legend shows that the hottest summer month extreme temperature spells (dark red) have temperatures of 35.34˚C to 42.13˚C and occur mostly in southern latitude or eastern EU countries. By contrast, the coolest summer month extreme temperature spells (dark blue) have temperatures of 16.37˚C to 28.77˚C and occur mostly in Scandinavia, the western UK, and Ireland. The map thus shows that temperatures can vary widely even in the summer months. Not shown in Fig. 1, our sample also includes extreme temperature spells that occur in the non-summer months.

[9] The side of a "tile" is 27.7 Km at the equator and broadly follows a cosine function depending on the latitude of the location. For example, the side of a London $0.25^\circ \times 0.25^\circ$ tile is 17.3 Km.

[10] Our measures of the intensity and duration of extreme temperature spells are both similar to and different from Addoum et al. (2020). They are similar because we both use the percentile threshold of a prior distribution by time of year and location to establish whether a temperature is extreme. They use the 90th percentile. We use the more stringent 95th percentile by season and grid location of the weather measurement. They then proceed to count *the number of days* in a period that the maximum temperature exceeds a threshold to measure the "temperature exposure on establishment-level sales" (Addoum et al. 2020, p. 1334). By contrast, we focus on the maximum of the temperatures that exceed the threshold within an extreme temperature (heat) spell, which we view as a measure of *temperature intensity*. An extreme temperature spell is one with two or more *consecutive* days where the maximum daily temperature exceeds the threshold. Thus, whereas they count any day with anomalous heat, we focus only on maximum temperatures within the days of extreme temperature spells. To measure duration, we count the number of days of extreme temperature (heat) spells within a year as a separate variable (*DURATION*).

[11] A *NUTS* (Nomenclature of Territorial Units for Statistics) code represents a territorial division within an EU country, the United Kingdom, or a related country (e.g., an EFTA country). As of January 1, 2018, there are 104 *NUTS1* regions and 277 *NUTS2* regions in the EU and the UK (https://ec.europa.eu/eurostat/web/nuts). *NUTS* divisions are mainly used to track goods and services subject to European legislation.

3.2 *Financial data*

We access BVD Orbis to extract sales, total assets, pretax earnings, and the book value of equity for 2011–2019 to generate our sample. The requirement for data on these variables maximizes the sample size (e.g., depreciation expense and cost of goods sold are missing for 36.1% and 95.3%, respectively, of the sample). We use Eikon Datastream to assign GICS sector codes and identify the headquarters location of these firms. We match the location of a firm to the location of an extreme temperature spell. To match the extreme temperature spells to firm-level financial performance, we aggregate the individual extreme temperature spell observations for each firm over each fiscal year. Specifically, we average the maximum temperature of the extreme temperature spells (denoted *SPELL_MAX_TEMP* in the empirical analysis) and sum the number of extreme temperature spell days for each firm-year (denoted *DURATION* in the empirical analysis). Where appropriate for a test, we average the maximum spell temperatures over a season rather than a year.

3.3 *Sample*

As shown in Table 1, this procedure generates a sample of a maximum of 559,077 firm-year observations with spell measures and financial statement data. Because of missing data for some financial variables, the tables indicate smaller sample sizes for the different regressions. The sample-wide average maximum spell temperature over 559,077 observations applies to all extreme temperature spell days in all years and locations. The maximum temperature of a spell on any day of the year in a particular location can be different. The sample-wide average maximum spell temperature at the 90th (10th) percentile of the spell measurements is 31.2˚C (17.9˚C).

Table 1 describes the sample. The means (standard deviations) for the financial variables in the regression models (Section 4) are as follows: sales-to-assets ratio = 0.87 (0.87) and net pretax income-to-sales ratio = 10 percent (25%). In addition, the mean (standard deviation) annual sum of extreme temperature spell days in a year = 16.8 (8.2) days. The percentage of missing observations for a variable is less than one percent. This should minimize any bias from missing data. We note three dominant countries in the dataset, namely, the UK, France (FR), and Germany (DE), which comprise 38.8 percent of the sample observations. In the empirical analysis, we examine *UK.FR.DE* observations separately as well as in combination with all the countries in the dataset. Due to Eikon Datastream and BVD Orbis coverage, the firm-years are reasonably evenly distributed within the study period, comprising about 50,000–60,000 per year over 2011–2019.

Table 2 indicates the correlations. Most correlations, in particular the correlations involving the weather variables of *SPELL_MAX_TEMP* and *DURATION* and the financial performance variables, are low, i.e., less than 10 percent. This suggests that the weather variables are as good as exogenous to financial performance. Some exceptions are shown in bold and explained as follows. (i) Corr. (*SALES_ASSETS*, *NI_SALES*) < 0. Sales is the denominator in *NI_SALES*. (ii) Corr. (*SPELL_MAX_TEMP, LATITUDE*) < 0. Low latitudes are hotter on average. (iii) Corr. (*SPELL_MAX_TEMP*, *SUMMER*) > 0. Summers have hotter extreme temperature spells. (iv) Corr. (*DURATION*, *SUMMER*) > 0. Summers have longer extreme temperature spells. (v) Corr. (*UK.FR.DE*, *NON-VULNERABLE*) > 0. Firms in the United Kingdom, France, and Germany are less vulnerable to climate change than firms in other countries. (vi) Corr. (*ENERGY, LABOR-INTENSIVE)* < 0. The energy sector is more capital intensive than labor intensive. Overall, these correlations are as expected. In the regressions, we capture the correlations through the marginal effects of the covariates and by including fixed effects and splitting the sample on firm, sector, season, country, and location.

4. Method

4.1 Financial performance and extreme temperature spells

We specify the following model for each firm-year observation.

$$FIN\_PERF = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon. \quad (1)$$

FIN_PERF = sales-to-total assets ratio (*SALES_TA*) or pretax profit-to-sales ratio (*NI_SALES*). *SPELL_MAX_TEMP* = the average maximum spell temperature in a year (in Celsius). *DURATION* = the sum of extreme temperature spell days in a year. *LEVERAGE* = one minus the ratio of common equity to *TA*, and *FE* = year and sector fixed effects to adjust for unrelated time trends and sector differences. For *FIN_PERF* = *SALES_TA*, we contend this reflects the impact of extreme temperature spells on financial performance through a customer demand and sales effort channel. We assume the ratio numerator (*SALES*) mainly captures customers' demand or firms' selling efforts in response to extreme temperature, as the denominator (*TA*) is the beginning-of-year balance sheet value of a firm's assets. For *FIN_PERF* = *NI_SALES*, we view this as the impact of extreme temperature spells on financial performance through a margin channel, which could respond to extreme weather as a change in sales or costs and expenses.

For *FIN_PERF* = *SALES_TA*, β_1 in Eq. (1) should be positive. By contrast, for the average sample firm, β_2 should be negative, indicating a hump-shaped curve. However, it could also be positive or insignificant for some firms (e.g., in high latitude locations, in the energy sector). We test for systematic cross-sectional differences. We estimate Eq. (1) with leverage as a control variable. We predict a positive relation between leverage and financial performance based on the notion that more efficient firms (e.g., with higher *SALES_TA* ratios) have a lower cost of bankruptcy (Margaritis and Psillaki 2007). There is no need to include total assets (*TA*) as a control because the left-hand side of Eq. (1) is already size adjusted. We predict a negative coefficient for *DURATION*, contending that longer extreme temperature spells should further degrade *FIN_PERF* incremental to *SPELL_MAX_TEMP*. However, if the effect of *DURATION* on *SALES_TA* is conditional on whether the extreme temperature spell occurs in normally cooler or hotter conditions, the β_3 coefficient for *DURATION* might not be significant.

We also expect the same signs for the Eq. (1) coefficients for *FIN_PERF* = *NI_SALES*, except that identification could be more difficult because the response of margin to extreme temperature spells combines the impact on costs and expenses and the impact on sales. On the one hand, because we already predict declining *SALES_TA* for extreme temperature spells above a critical temperature, should costs increase in response to extreme heat (e.g., due to degraded infrastructure, biological or physiological factors, or workplace productivity), then we would observe $\beta_2 < 0$ for *FIN_PERF* = *NI_SALES*. On the other hand, it is less clear that profit margin would increase for extreme temperature spells below a critical temperature (i.e., for $\beta_1 > 0$) because, for $\beta_1 > 0$, costs would have to decline faster than sales increase, which seems unlikely.

4.2 Cross-sectionals

We explore how the β_1 and β_2 coefficients vary for different partitions of the sample. We consider eight possible differences: (i) Because energy firms can benefit from extreme temperature spells, they should not experience a decrease in sales during spells with temperatures above a critical level, that is the β_2 coefficient should not be negative. (ii) If spell temperature affects labor productivity, the effects of extreme heat on labor-intensive firms should be stronger. (iii) Firms in low latitudes (versus high latitudes) should be more intensely affected by extreme temperature spells. (iv) Extreme temperature spells during weekdays (when firms are more active), (v) during the summer months (when extreme temperature spells are more intense), and (vi) in climate-change vulnerable countries should also have stronger effects. (vii) Firms with fewer subsidiaries have stronger effects based on the idea that these are firms whose operations are likelier to be closer to their headquarters location, whereas firms with more subsidiaries would have operations in many locations, including other countries, such that headquarters location for these firms may only reflect a portion of their operations and customer location. (viii) Lastly, we partition the sample into firms with headquarters more than 100 km from the closest capital city in the EU or London and those less than 100 km from the closest capital city. We motivate this distinction on the idea that the capital cities of the EU countries and London should have higher resilience and thus more ability to mitigate the effects of extreme temperature (and climate change) compared to other locations.

4.3 Extreme temperature spells and duration

To test whether extreme temperature spell duration affects financial performance directly or interacts with spell temperature, we specify the following regression.

$$FIN\_PERF = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP \times DURATION + \beta_3 SPELL\_MAX\_TEMP^2 + \beta_4 SPELL\_MAX\_TEMP^2 \times DURATION + \beta_5 DURATION + \beta_6 LEVERAGE + FE + \varepsilon. \quad (2)$$

Consistent with H3, for *FIN_PERF = SALES_TA,* we expect $\beta_2 > 0$ and $\beta_4 < 0$ in addition to $\beta_1 > 0$ and $\beta_3 < 0$, which in essence is a prediction that the hump shape as per Eq. (1) is humpier for spells of longer duration. We also explore the sensitivity of the inflection point of the sales-to-temperature response to longer versus shorter extreme temperature spells.

5. Results

5.1 Sales-to-assets ratio

We start with Fig. 2.1, which is the main finding from Eq. (1). This plots the sales-to-temperature response function over the range of *SPELL_MAX_TEMP* from 15˚C to 35˚C for the sample-wide regression estimates from Regr. 1 of Table 3. The range of *SPELL_MAX_TEMP* from 15˚C to 35˚C reflects high temperature spells that occur in both normally in hot and cold months and normally hot and cold countries. In the graph, *LEVERAGE* is held constant at the sample mean (Table 2). The curve is clearly hump shaped, and the sample-wide maximum spell temperature at the inflection point is 23˚C (shown in black). From the curvature of Fig. 2.1, we can calculate the response of sales to a change in maximum spell temperature. While the shift in sales of a change in 1˚C from 23˚C in either direction is small, if the maximum spell temperature (*SPELL_MAX_TEMP*) were to exceed the sample-wide average by, say, 5˚C, Eq. (1) estimates that the sample-wide sales-to-assets ratio would decrease by 2.0 percent. A shift of 5˚C is potentially realistic for investors and creditors. For example, in July 2022 the UK experienced a heat wave of over 40˚C, or a shift of more than 10˚C above the normal UK *summer* heat wave temperature of 28˚C to 30˚C.[12] Also, in February, the UK experienced record-breaking unusually warm winter extreme temperatures, which in London was at least 10˚C above the average normal February temperature of 9˚C.

Figure 2.2 graphs the inflection points of the sales-to-temperature response function for the sample as a whole (shown in black) and for different partitions of the sample. For most of the sample, the sales-to-temperature response function turns from positive to negative within a narrow band of maximum spell temperature. Descriptively, higher inflection points occur for labor intensive firms, on weekdays, when the firm has fewer subsidiaries, in low latitude countries, in the summer months, and in the UK, France, and Germany. For firms in high latitude countries and the energy sector, the slope of the response function is positive over the relevant range of spell temperatures. As such, the inflection point, if any, is outside of the relevant range of spell temperatures. For firms in non-climate change vulnerable countries, the inflection point is also outside of the relevant range of maximum temperatures, possibly because a significant portion of the firms in non-vulnerable countries are in the United Kingdom, France, Germany (Pearson corr. *UK.FR.DE*, *HIGH_LATITUDE* = 0.555 (Table 2)) and the high latitude Scandinavian countries.

Table 3 summarizes the regression statistics from estimating Eq. (1) for *SALES_TA*. Regr. 1 shows our main result. Consistent with a hump-shaped sales-to-temperature response, the data indicate positive and negative coefficients ($p<0.01$) for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2}, respectively. These findings support H1 and H2 for the sales-to-assets

[12] It is important to view *SPELL_MAX_TEMP* as representing variation inherent in the time and location of a wide range of maximum extreme temperature spells, which are extreme by reference to what is statistically well outside the range of normal temperature by time and place. Conversely, viewing an increase in *SPELL_MAX_TEMP* in terms of one's local or business experience and reactions to weather or as an increase in normal temperature (rather than an increase in maximum spell temperature) runs the risk of misinterpreting the results of this study. Even in the UK, the Met Office reports that there has been a dramatic shift in the maximum temperature in the past 20 years in most locations in the UK (https://www.carbonbrief.org/media-reaction-uks-record-breaking-winter-heat-in-2019/). We discuss further in Appendix A the definition of an extreme high temperature spell and how to interpret the response of the sales-to-assets ratio to variation in *SPELL_MAX_TEMP*.

ratio. Regarding the other variables in Regr. 1, the coefficient for *DURATION* is not significantly different from zero. We also find that more leveraged firms have stronger sales performance. This is consistent with prior research suggesting that because more efficient firms are less threatened by bankruptcy they can acquire more debt (Margaritis and Psillaki 2007). *LEVERAGE* varies positively ($p<0.01$) with *SALES_TA* in all the regressions in Table 3.

Table 3 explores the sales-to-temperature response function for several subsamples. First, we show positive and negative coefficients ($p<0.01$) for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2}, respectively, for non-energy firms (Regr. 6) but not for energy firms (Regr. 2). A *t*-test of the coefficient difference suggests that the curvature of the sales-to-assets ratio response to spell temperature is significantly different ($p<0.10$) for energy firms. Second, while the Regr. 3 and Regr. 7 response curves are both hump shaped, extreme spell temperature has a greater differential impact on the sales performance of firms in labor-intensive (Regr. 3) versus non-labor-intensive sectors (Regr. 7). These stronger results for labor-intensive vs. non-labor-intensive firms are consistent with the view that extreme temperature spells in normally hotter conditions reduce employee productivity. Third, the hump-shaped response functions for *UK.FR.DE* firms (Regr. 4) and non-*UK.FR.DE* firms (Regr. 8) are both hump shaped with similar curvature. Fourth, Regr. 5 shows that firms in low-latitude locations reflect a hump shape, whereas the opposite is true for high-latitude firms (Regr. 9). The differences in *SPELL_MAX_TEMP*^{2} and *SPELL_MAX_TEMP*^{2} are significantly positive ($p<0.01$) and negative ($p<0.01$), respectively. This is consistent with the view that high-latitude firms benefit more from rising temperatures. Fifth, Regr. 10 shows that extreme temperature spells on weekdays have stronger effects on sales in both directions versus on weekends (Regr. 14). This potentially occurs because weekdays in many countries generate more business than weekends. Sixth, because the temperature extremes are different, maximum spell temperature has a significant differential impact on the sales-to-temperature response function for the summer versus the non-summer months (Regrs. 11 and 15). Specifically, the coefficient for

SPELL_MAX_TEMP is more positive for summer extreme temperature spells ($p<0.10$) and the coefficients for *SPELL_MAX_TEMP*^{2} are significantly negative for both partitions. Seventh, the coefficients are significantly different for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} for firms with fewer subsidiaries versus more subsidiaries in the group (Regrs. 12 and 16). This result supports the idea that firms with fewer subsidiaries are more directly affected by the weather conditions of the company's headquarters. Eighth, firms in climate-change-vulnerable versus non-vulnerable countries (Regrs. 13 and 17) reflect a humpier curve. That is, the coefficients for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} for firms in climate-change vulnerable countries compared to firms in less vulnerable countries are both significantly different from zero ($p<0.01$) and significantly different from each other.

Overall, the statistics in Table 3 and the graphs in Fig. 2 provide strong evidence of a curvilinear relation between sales performance and spell maximum temperature for the average sample company, with an inflection point of about 23˚C.[13] The individual regressions also show significant differences in the shape of the sales-to-temperature response function largely consistent with our conceptual arguments.

5.2 Pretax profit-to-sales ratio

Table 4 summarizes the results for Eq. (1) of whether extreme high temperature spells affect firms' pretax profit margin (*NI_SALES*) as a hump-shaped response. Regr.1 of Table 4 shows the coefficients for the full sample. For *NI_SALES*, we do not observe the same significant coefficients for *SPELL_MAX_TEMP* as we do for *SALES_TA*. The coefficient for *SPELL_MAX_TEMP*^{2}, nonetheless, is significantly negative ($p<0.10$). The coefficient for *SPELL_MAX_TEMP*^{2} is also mostly negative and significant for the subsamples. In other

[13] While this temperature level applies to the entire sample (multiple countries in multiple latitudes), the literature on building design also indicates that indoor work productivity begins to degrade at temperatures starting around 24˚C (Kekäläinen et al. 2010). Since an indoor work environment is less affected by natural temperature variation from latitude, this lends credence to our sample-wide inflection point of around 23˚C (and an inflection point of 23.3˚C for the labor-intensive firms in our sample). Studies of labor productivity (Zhang and Shindell 2021; Zivin and Neidell 2014) also find that the allocation of time to labor declines linearly in extreme temperature above a baseline threshold of 76˚F–80˚F (24.4˚C–26.6˚C).

words, the slope of the profit margin-to-temperature response function is uniformly negative over the hotter sections of maximum spell temperature. Thus, the coefficients for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} indicate that profit margin does not increase in extreme temperature spells in normally cooler conditions but decreases at an increasing rate in extreme temperature spells in normally hotter conditions. For profit margin to increase in extreme temperature spells in normally cooler conditions would be a tall order, however, as sales are already increasing under such conditions as per Table 3. In other words, for margin to increase, costs and expenses would have to decline at a faster rate than sales increase. Although employees could become significantly more productive to offset the increase in sales in extreme temperature spells in normally cooler conditions, empirically, the findings in Table 4 show no evidence of this effect.

Table 4 also reports tests of the differences in the *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} coefficients. First, as predicted, we find a significantly more negative slope ($p<0.10$) for non-energy firms (Regr. 6) versus energy firms (Regr. 2) and a significantly more negative slope ($p<0.10$) for labor-intensive firms (Regr. 3) versus non-labor-intensive firms (Regr. 7). Second, the slope of the margin-to-temperature response function is also systematically more negative for weekday versus weekend extreme temperature spells but not for climate vulnerable versus climate non-vulnerable countries. Third, we note a difference in the sign of the coefficients for *DURATION* in Table 4, which are mostly significantly positive, and the signs of the coefficients for *DURATION* in Table 3, which are mostly insignificant. Given that *SALES_TA* is largely unresponsive to *DURATION*, this difference most likely associates with costs and expenses other than those explained by variation in extreme temperature level. Hence, assuming that the effect of extreme temperature on costs is incorporated into the coefficients for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} in Eq. (1) with *NI_SALES* as the dependent variable and that the remaining component of profit margin is a cost reduction, then longer extreme temperature spells will logically associate with a larger cost reduction and, hence, a higher level of pretax margin. Consistent with this view, when we replace *NI_SALES* with *NI_TA* in Eq. (1), the coefficients for *DURATION* are insignificant for all regressions. Lastly, we find that more leveraged firms have lower profit margins. This result of a negative coefficient for *LEVERAGE* is consistent with the "pecking order theory" in finance, namely, the well-established practice that most firms finance first with internal funds, next with debt, and then with equity. This ordering of financing choices creates a negative relation between leverage and profitability (Myers and Majluf 1984; Rajan and Zingales 1995).

5.3 Impact of extreme temperature spell duration

5.3.1 Sales-to-assets ratio. We consider an alternative to Eq. (1) as the model to explain the relation between financial performance and extreme temperature spells. Stated as Eq. (2), this alternative model states that extreme temperature spell duration interacts with spell temperature to magnify the improvement in financial performance in normally cooler temperatures (e.g., on the upside of the sales-to-temperature response function) and worsen the deterioration of financial performance in normally hotter temperatures (e.g., on the downside of the sales-to-temperature response function). Table 5 summarizes the results of estimating Eq. (2) with *SALES_TA* as the dependent variable for the full sample and the partitions examined earlier.

We first present the sales-to-temperature response function for different levels of spell duration as Fig.3. Fig. 3.1 shows the hump shape based on the sample-wide coefficients in Regr. 1 of Table 5. Fig. 3.1 clearly shows that the falloff in sales for longer spells (*DURATION* = 35 days) occurs at a steeper rate (the blue line) than for shorter spells (*DURATION* = 15 days) (the dotted line). Fig. 3.2 then explores whether the maximum spell temperature after which sales begin to decline (inflection point) differs or is approximately the same for longer versus shorter spells. The figure indicates that the sample-wide spell temperature after which sales begin to decline is less than one degree (0.72˚C) higher for extreme high temperature spells of shorter versus longer duration.

Table 5 summarizes the results of estimating Eq. (2). Focusing on the full sample, Regr. 1 shows significantly positive coefficients for *SPELL_MAX_TEMP* ($p<0.10$) and *SPELL_MAX_TEMP* × *DURATION* ($p<0.05$) and significantly negative coefficients for *SPELL_MAX_TEMP*^{2} ($p<0.10$) and *SPELL_MAX_TEMP*^{2} × *DURATION* ($p<0.05$). The coefficients for *SPELL_MAX_TEMP* × *DURATION* and *SPELL_MAX_TEMP*^{2} × *DURATION* are mostly significantly positive and negative, respectively, for the sample partitions. We also explore the direct effect of *DURATION* on *SALES_TA*. The economic effect of *DURATION* is small, however, compared to the effect of the interaction of duration and spell temperature. For example, based on Regr.1 of Table 5, the coefficient for *DURATION* of -0.0194 ($p<0.05$) changes the sample-wide level of the *SALES_TA* ratio by at most 0.07 for *DURATION* = 15 days versus 35 days (incremental to *SALES_TA*, *SPELL_MAX_TEMP* × *DURATION*, and *SPELL_MAX_TEMP*^{2} × *DURATION*).

As an additional partitioning variable, Table 5 shows the sensitivity of the results to Distant (Regr. 12) and Close (Regr. 16). To create this partition, we first measure the closest distance of each firm's headquarters to London or an EU capital city. We then split the sample into firm headquarters that are within 100 km of London or an EU capital city (Close) or not within 100 km of London or an EU capital city. We reason that firms closest to one of these major cities would likely be more protected from heat waves by physical infrastructure (e.g., transportation, buildings) for the benefit of employees and customers. Thus, the sales-to-temperature response function should be humpier in Distant versus Close locations. The significant coefficients for *SPELL_MAX_TEMP* × *DURATION* and *SUM_MAX_ TEMP*^{2} × *DURATION* in Regr. 12 versus Regr. 16 support this idea. In sum, extreme temperature spell duration has the effect of sharpening the hump of the sales-to-temperature response function but does little to shift the inflection point of the curve at which sales begin to decline in response to extreme temperature.

Overall, these results support H3: that longer (shorter) extreme temperature spells intensify (weaken) the curvilinear response of financial performance to extreme temperature spells.

5.3.2 Pretax profit margin. We also estimate Eq. (2) for pretax profit margin as the dependent variable and show the results graphically in Fig. 4. We show the sample-wide results (Fig. 4.1) and three partitions of the sample that are more likely than the others to be affected by a heat wave, namely, firms with few subsidiaries, firms distant from a major metropolitan area, and firms subject to extreme temperature spells in summer. Fig. 4 shows two key results. First, pretax profit margin (*NI_SALES*) declines nonlinearly as the extreme temperature of a spell (*SPELL_MAX_TEMP*) increases. This occurs over a wide range of spell maximum temperatures (from 15˚C to 35˚C). Second, pretax profit margin is higher for firms exposed to longer spells with lower extreme temperatures (Figs. 4.1–4.4) and the same (Figs. 4.1 and 4.2) or lower (Figs. 4.3 and 4.4) for firms exposed to longer spells with higher extreme temperatures. The economic effects are significant. Based on Fig. 4.1, if the maximum spell temperature were to exceed the sample-wide average of 23˚C by 5˚C, the pretax profit margin would decrease by 12.9 percent for *DURATION* of 15 days.

Overall, these findings suggest that when the extreme temperature spells are longer and occur at times of normally cooler conditions, firms have higher pretax profit margins than when the extreme temperature spells are shorter. Hence, firms are more profitable (e.g., able to operate at lower cost) in spells of lower temperature. The graphs (and untabulated regressions) also indicate that firms have higher margins when the lower extreme temperature spells are of longer duration.

5.4 Impact of extreme temperature spells on the sales-to-assets ratio over time

Table 6 examines the temporal pattern of the *SPELL_MAX_TEMP* and *SPELL_MAX _TEMP*^{2} coefficients by estimating Eq. (1) for *SALES_TA* for three successive periods and the two partitions of the sample potentially most different in their exposure to the effects of extreme temperature spells: (i) firms with a small number of subsidiaries and (ii) firms distant from London or a European capital (other results available on request). A comparison over time of these partitions could indicate whether our results reflect a trend. Table 6 also shows that the differences in the coefficients for the partitions for *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} are mostly positive and negative, respectively, in each of the three periods but with no clear trend. In addition, we estimate Eq. (2) for *SALES_TA* for three successive periods to check whether the effect of duration on *SALES_TA* through its interaction with *SPELL_MAX_TEMP* changes over time. In an untabulated analysis, we find that the coefficients for *SPELL_MAX_TEMP* × *DURATION* and *SPELL_MAX_TEMP*^{2} × *DURATION* are positive and negative, respectively, also with no clear trend. Thus, we find no evidence that the sales to extreme temperature spell response function has changed over time.

5.5 Impact of extreme temperature spells on ROA

Because extreme temperature spells impact *SALES_TA* as a hump shape (Table 3 and Fig. 2) and *NI_SALES* as a curvilinear negative relation (Table 4 and Fig. 4), the product of the two ratios should also reflect a curvilinear relation, especially as *TA* and *SALES* are positively related through the effect of firm size (e.g., the Pearson corr. (*Log_TA*, *Log_SALES*) = 0.34 for our dataset). To explore the shape of the *ROA*-to-temperature response function, we estimate Eq. (2) with *NI_TA* as the dependent variable. Fig. 5 plots the response function for *ROA* for the full sample and the same three partitions of the sample as shown in Fig. 4. Overall, *ROA* (*NI_TA*) increases nonlinearly in extreme temperature spells in only the lowest spell maximum temperatures and then decreases nonlinearly as the maximum spell temperature (*SPELL_MAX_TEMP*) increases (Figs. 5.1–5.4). As an economic effect, based on Fig. 5.1, if the maximum spell temperature were to exceed the sample-wide inflection point of 23˚C by, say, 5˚C, the pretax ROA for the average sample firm would decrease by 7.7 percent for average *DURATION* of 15 days.

6. Effects of extreme temperature spells on ESG performance and carbon emissions

Given that spells with extreme maximum temperatures above the inflection point decrease sales, profit margins, and return on assets, a natural follow-on question is whether managers act to alleviate these risks. They may do so by streamlining their operations to moderate the impact of extreme heat on employee productivity and sales effort, investing in environmentally resilient infrastructure, or improving their supply chains and governance policies to manage carbon emissions. Additionally, new business strategies may be implemented (Coonan 2023). Extreme temperature spells could also increase emissions because electricity demand surges during such times, often requiring grid operators to resort to coal and oil-fired power, which then prolongs the life of otherwise uneconomic fossil fuel power plants, further contributing to emissions. Since we cannot observe managers' actions to mitigate the impact of heat waves directly, we follow prior work and examine two possible proxies of managers' actions: firms' future ESG performance (de Villiers et al. 2011; Walls et al. 2012) and emission levels (Alam et al. 2019). If managers' actions mitigate or neutralize the firm from the risks of extreme temperature spells, future ESG performance should improve (Zheng et al. 2022) and/or emissions should decrease (Chen and Chen 2021; Li et al. 2021) or at least not be responsive adversely to extreme temperature spells. Conversely, if managers were to adopt a business-as-usual response to extreme temperature spells or not attend to these risks, the outcomes should be reflected in declining ESG performance or ESG growth and/or an increase in emissions in the future that varies with spell temperature. To test this idea, we estimate the following regression:

$$\Delta ESG\_SCORE \text{ or } \Delta EMISSIONS = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon. \quad (3)$$

To identify firms that might take actions after extreme temperature spell events, ΔESG_SCORE is the change in a firm's *ESG_SCORE* from *t-1* to *t*+3 (specifically, the change in Refinitiv's ESG score of between 0 and 100 (Refinitiv 2022)), and $\Delta EMISSIONS$ is the change in carbon emissions from *t-1* to *t*+3 (specifically, the change in the sum of Scope 1, 2, and 3 emissions accessed from the Institutional Shareholder Services (ISS) Carbon Footprint dataset (ISS 2022)). Year *t* is the year of measurement of *SPELL_MAX_TEMP* and the other variables. We use a four-year interval – from the end of *t*-1 to the end of *t*+3 – to allow a firm to invest in and potentially benefit from operating policies designed to build resilience to more frequent and intense extreme weather in the future. To capture economic shocks that affect Δ*ESG_SCORE* or Δ*EMISSIONS* apart from those related to the covariates, Eq. (3) controls for firm-level fixed effects. As an additional test, we state Δ*EMISSIONS* in Eq. (3) as the change in emissions intensity, defined as the change from year *t*-1 to *t*+3 in the sum of Scope 1, 2, and 3 emissions divided by sales revenue.

6.1 Effects on ESG performance

If extreme temperature spells were to affect the future change in ESG score as a hump shape, the coefficients for β_1 and β_2 in Eq. (3) should be positive and negative, respectively. That is, the future change in ESG score should be lower for extreme temperature spells with higher versus lower maximum temperatures. Table 7 summarizes the results for Δ*ESG_SCORE*. To illustrate the ESG response function, Fig. 6 plots the sample-wide percentage change in ESG score for different levels of extreme temperature based on the coefficients for Regr. 1 of Table 7 (excluding adjustments for firm-level fixed effects).[14] The coefficients for *SPELL_ MAX_TEMP* and *SPELL_MAX_ TEMP*^{2} are significantly positive and negative, respectively, for the full sample (Regr. 1) and most of the subsamples. These coefficients, as reflected in Fig. 6, show that the growth in ESG score is curvilinear and declines at an increasing rate as the maximum spell temperature increases. As an economic impact, if the maximum spell temperature were 28˚C instead of 23˚C, the sample-wide increase in ESG score would drop from 3.94 to 3.30, or a relative drop of 16.4 (rounded) ((3.297-3.943)÷3.943) percent. ESG

[14] Note that the regressions employ smaller sample sizes than in the earlier tables because the ESG scores and emissions data are available for only a small number of publicly traded firms in the dataset.

performance, thus, improves less for extreme temperature spells that occur when temperatures are unusually high (i.e., 28˚C instead of 23˚C).

Together, these findings indicate a negative association between the future change in ESG score and extreme temperature spells. They are also consistent with the view that managers do not appear to act to build resilience to the effects of extreme temperature spells on sales, margins, and profits. If they did, the β_1 and β_2 in coefficients in Table 7 would not be responsive to spell temperature, that is, the change in ESG score would not vary systematically with spell maximum temperature.

6.2 Effects on carbon emissions

Table 8 summarizes the sample-wide results for Δ*EMISSIONS* (Regr. 1) and the partitions analyzed earlier. The β_1 and β_2 in coefficients for Regr. 1 are significantly negative and positive, respectively ($p<0.05$), indicating a U-shaped curve. Fig. 7 plots the sample-wide change in emissions from year *t-1* to *t*+3 for different levels of extreme spell temperature. The U-shaped plot shows that while the change in Scope 1, 2, and 3 emissions from year *t-1* to *t*+3 declines for cooler extreme temperature spell maximum temperatures (in the 15˚C to 25˚C range), the emission changes are positive for extreme temperature spells with hotter maximum temperatures (in the 26˚C to 35˚C range). Based on the coefficients of Regr. 1 of Table 8, if the extreme temperature spells were those with maximum temperatures of 29˚C, average Scope 1, 2, and 3 emissions would increase by 359,165 metric tons. By contrast, if extreme temperature spells were those with maximum temperatures of, say, 23˚C, average Scope 1, 2, and 3 emissions would decrease by 180,912 metric tons. Fig. 7, thus, shows that for extreme temperature spells with temperatures of 26˚C or more, future emissions increase. In other words, when hotter extreme temperature spells occur, the plot suggests that it can be more difficult for a firm to decrease its emissions, possibly because extreme temperature spells with high maximum temperatures require more and costlier energy to maintain operations. By contrast, if extreme temperature spell maximum temperatures were to have no impact on emissions in the future (e.g., because managers take actions to mitigate the positive impacts), future emission changes would be unresponsive or respond negatively to extreme temperature spell temperature, i.e., the response curve would be essentially flat or possibly negatively sloped across the full range of temperatures.[15]

7. Robustness Tests

7.1 Controlling for country-level sales

A potential concern is that the effects of extreme high temperature spells on financial performance reflect a common or country-wide component, such that when an extreme temperature spell occurs in the same location as a firm in a particular country, all firms' ratios in the same country are degraded similarly, for example, due to peer-to-peer linkages in a country's economy. To test for this possibility, we estimate Eq. (3).

$$SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + \beta_5 WHOLESALE\_RETAIL + FE + \varepsilon. \tag{4}$$

WHOLESALE_RETAIL = retail and wholesale sales in each country of location in year *t* scaled by the beginning of year average total assets of firms in each country of location, and the other variables are defined as before. While Supplementary Table A1 shows that firm-level sales are highly correlated with country-level sales ($p<0.01$), the coefficients for *SPELL_MAX_TEMP* and $SPELL\_MAX\_TEMP^2$ remain significantly positive and negative similar to the findings in Table 3. To test whether firms' response of financial performance to extreme temperature spells might be confounded by the performance of a country's agricultural sector, we also modify Eq. (3) by replacing *WHOLESALE_RETAIL* with *AG_PERCENT* (the percentage of agriculture GDP to total GDP in a country). The results in Table 3 do not change appreciably.

We next estimate Eq. (4) after replacing *WHOLESALE_RETAIL* with *NUTS1_MAX_TEMP* and $NUTS1\_MAX\_TEMP^2$ or *NUTS2_MAX_TEMP* and $NUTS2\_MAX\_TEMP^2$, where

[15] We also examined whether firms' *emissions intensity* defined as the change in the sum of Scope 1, 2, and 3 emissions scaled by sales revenue from year *t*-1 to *t*+3 varies with extreme temperature spell maximum temperature. In an untabulated analysis, we find a pattern similar to Fig. 7. The regression coefficients for the shape of the curve are not significantly different from zero in this analysis.

we match each firm to its *NUTS1* or *NUTS2* code. Because these codes represent a territorial division within an EU country that can be linked to the location of a firm's headquarters, they are a finer partition of the impact that a common or country-level weather factor would have on firm-level financial performance. An untabulated analysis shows significant positive and negative coefficients for *SPELL_MAX_TEMP* and $SPELL\_MAX\_TEMP^2$ after controlling for the average extreme temperature spell maximum temperature in a firm's *NUTS* division (either *NUTS1_MAX_TEMP* or *NUTS2_MAX_TEMP*), which is much broader than firm headquarters location but narrower than country location. The coefficients for the *NUTS1or2_SPELL_ MAX_TEMP* and $NUTS1or2\_SPELL\_MAX\_TEMP^2$ variables are also positive and negative, respectively. Thus, our main findings hold after controlling for country-level wholesale and retail sales, agricultural GDP, and the average extreme temperature spell temperature in a firm's *NUTS* division.

7.2 Group size as a proxy for firm-level diversification

The location of firm headquarters to measure the impact of extreme temperature spells on firm performance does not distinguish between firms with operations in a single weather location (i.e., the same location as the firm's headquarters) versus multiple locations, possibly including several countries. Ideally, we would like to have the location of firms' subsidiaries and their sales and profits. Not having firms disclose this information works against finding positive coefficients, so a better measure of sales and expenses around the event location would likely show stronger effects. Having already addressed this based on the number of subsidiaries in the consolidated group, we also test the effect of group size as an interaction effect.

$$SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 GROUP\_SIZE + \beta_3 SPELL\_MAX\_TEMP \times GROUP\_SIZE + \beta_4 SPELL\_MAX\_TEMP^2 + \beta_5 SPELL\_MAX\_TEMP^2 \times GROUP\_SIZE + \beta_6 DURATION + \beta_7 LEVERAGE + \beta_8 WHOLESALE\_RETAIL + FE + \varepsilon. \quad (5)$$

GROUP_SIZE is equal to one if the number of firms in the group (consolidated entity) is greater than the sample median by year, otherwise zero. Supplementary Table A2 shows that the coefficients for the full sample for *SPELL_MAX_TEMP* and $SPELL\_MAX\_TEMP^2$ are significantly positive and negative ($p<0.01$), respectively, thus confirming the hump shape of the sales-to-temperature to response function. In addition, the coefficient for *GROUP_SIZE* × *SPELL_MAX_ TEMP* is significantly negative ($p<0.05$), and the coefficient for *GROUP_SIZE* × *SPELL_MAX_ TEMP*^{2} is significantly positive ($p<0.05$). This indicates that the hump shape is smoother for firms with diversified operations (*GROUP_SIZE*=1). That is, we find stronger effects for firms with fewer subsidiaries, assumed to have their operations and customers closer to firm headquarters.

7.3 Impact threshold analysis of confounding variables (ITCV)

In addition to an analysis of sub-samples to check for variation in the response of financial performance to spells of extreme temperature and the inclusion of sensitivity tests based on alternative designs and additional covariates, we investigate the potential for an endogenous omitted covariate to explain the extreme temperature response function based on impact threshold analysis (ITCV).[16] The goal of ITCV is to assess whether an omitted variable correlated with the covariates in the model might be confounding the outcome variable, in this case, the sales-to-assets ratio. It has also been shown to have advantages over instrumental variables regression (Busenbark et al. 2021; Larcker and Rusticus 2010).

To implement ITCV, we specify *SALES_TA* and *SPELL_MAX_TEMP* as the focal variables. We then calculate the minimum correlations necessary to alter the inference that *SALES_TA* is responsive to *SPELL_MAX_ TEMP* (and *SPELL_MAX_TEMP*^{2}) due to an excluded covariate. Following, Larcker and Rusticus (2010), we proxy for the minimum correlation necessary to alter the causal inference due to omitted covariates using the remaining covariates in the model, namely, *DURATION* and *LEVERAGE*.

[16] For example, if some firms switch their operations to a new location expecting a different pattern of extreme temperature, then *SPELL_MAX_TEMP* could in part represent a firm's choice of location rather than an exogenous event. As such, even though the evidence suggests that firm relocation does not improve the dependent variable of financial performance (Gregory et al. 2005; Laamanen et al. 2012), it could still represent an omitted covariate that is correlated for some firms with *SPELL_MAX_TEMP*.

Supplementary Table A3 summarizes the ITCV tests applied to the regressions in Table 3. The table states (i) the percentage of cases needed to be measured with bias so that the coefficient for *SPELL_MAX_TEMP* in Eq. (1) is insignificantly different from zero and (ii) the minimum threshold partial correlations as a function of the correlations between *SALES_TA* and *SPELL_MAX_TEMP* and between *SPELL_MAX_TEMP* and the remaining covariates in Eq. (1) such that an omitted covariate could invalidate the inference that the coefficient for *SPELL_MAX_TEMP* in Eq. (1) is non-zero.

For example, the first set of results for "All" observations in Col. A of Supplementary Table A3 indicates that 56.3 percent of the *SPELL_MAX_TEMP* observations would have to be replaced with biased observations to invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is non-zero. Similarly, 57.94 percent, 96.04 percent, and 87.06 percent of the other covariates would have to be biased to invalidate the same inference. While there is no ideal cutoff, on balance, higher percentages indicate a lower likelihood that the inference that the coefficient for *SPELL_MAX_TEMP* is zero is valid. As expected, the percentages are mostly high for the 16 partitions. Those that are low are low for a reason, however, as they are predictably associated with insignificant *SPELL_MAX_TEMP* coefficients (i.e., *UK_FR_DE*=19.35% for Regr. 4 of Table 3; Weekend=17.83% for Regr. 14 of Table 3; and High Group=9.610% for Regr. 16 of Table 3).

The second set of results in Col. B of Supplementary Table A3 refers to the minimum threshold partial correlation that an *omitted* covariate would need to have with the dependent variable (*SALES_TA*) to invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is non-zero. The first percentage is the minimum threshold partial correlation that an omitted covariate would have with the *dependent* variable (*SALES_TA*) to invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is non-zero. The second set of percentages refers to the equivalent minimum threshold partial correlations associated with the other covariates in the regression model. If either of the correlations for *DURATION* or *LEVERAGE* exceeds the threshold percentage for *SPELL_MAX_TEMP*, this increases the chances that an omitted covariate other than the predictor of interest (i.e., *SPELL_MAX_TEMP*) could explain the results. For example, for the first set of results in Column B of Supplementary Table A3, the partial correlation for *SPELL_MAX_TEMP* of 1.00 percent exceeds the partial correlations for *DURATION* or *LEVERAGE* of 0.045 percent and 0.003 percent, respectively. Thus, the chance that an omitted covariate other than the predictor of interest (i.e., *SPELL_MAX_TEMP*) could explain the findings is low. Note that because $SPELL\_MAX\_TEMP^2$ is functionally related to *SPELL_MAX_TEMP*, $SPELL\_MAX\_TEMP^2$ is not considered as a covariate whose partial correlation could invalidate the findings.

The main takeaway from Supplementary Table A3 is that we observe a small number of cases (6 out of 36) (marked in bold in cols. B) where the *SPELL_MAX_TEMP* threshold is exceeded. Thus, the likelihood is low that an omitted confounding covariate that could potentially invalidate the finding that the coefficient for *SPELL_MAX_TEMP* is non-zero (when our findings indicate that the coefficient for *SPELL_MAX_TEMP* is non-zero). Moreover, in two of the six cases (*UK.FR.DE* and Weekend), our Table 3 findings indicate that the coefficient for *SPELL_MAX_TEMP* is insignificantly different from zero (and thus need not meet the threshold). In sum, adding credibility to our main findings, ITCV tests suggest that the chance that an unknown omitted covariate correlated with *SPELL_MAX_TEMP* is driving the findings is low.

7.4 Placebo tests of the sales-to-temperature response function

We conduct placebo tests to further challenge the validity of our research design. The underlying logic is that they should not support our main result, namely, that *SALES_TA* responds to spells of extreme temperature as a curvilinear or hump-shaped relation. We conduct two kinds of tests. First, we replace the original covariate *SPELL_MAX_TEMP* in Eq. (1) with a temperature variable that logically should not drive a hump-shaped sales response similar to our main result. As two pseudo-covariate candidates, we (i) randomly reassign each

SPELL_MAX_TEMP observation to a different firm-year and (ii) induce random variation into each original *SPELL_MAX_TEMP* observation based on a normal distribution. In both cases, the pseudo covariates are designed to have the same standard deviation, a necessary condition, since otherwise a null result could occur if the placebo test were underpowered. We also include the square of the pseudo-covariate in the regression. Second, we replace the outcome variable in Eq. (1) with a variable that logically should not be responsive to an extreme temperature event. As two pseudo-outcomes, we select a pseudo measure of *SALES_TA* created by randomly reassigning each *SALES_TA* observation to a different firm-year and depreciation expense (for firms with non-missing values). Since depreciation expense is based on the historical cost of firms' assets purchased in earlier years, it should not logically be responsive to a temperature extreme. Neither should a random measure of *SALES_TA*.

Supplementary Analysis Figure A presents the results. The graphs plot the sample-wide dependent variable based on the regression coefficients for Eq. (1) modified using the placebo variables. The original findings from Fig. 2.1 are shown as the hump-shaped orange line for comparison. Based on untabulated analysis, we document that for each of Supplementary Analysis Figs. A1–A4, the coefficients for the pseudo versions of *SPELL_MAX_TEMP* and *SPELL_MAX_TEMP*^{2} based on Eq. (1) as modified using the placebo variables are insignificantly different from zero ($p<0.05$). As such, none of the placebo tests supports our main result, namely, that firm-level sales performance responds to spells of extreme temperature as a hump-shaped relation. Fig. A1 shows that the sales-to-extreme temperature response function is flat when we assume that *SPELL_MAX_TEMP* is generated by randomizing the row order of the original *SPELL_MAX_TEMP* observations. Fig. A2 shows that the sales-to-extreme temperature response function is slightly positive (but statistically insignificant based on regression tests) when we assume that *SPELL_MAX_TEMP* is generated by adding random variation to the original *SPELL_MAX_TEMP* observations. Fig. A3 shows that the sales-to-extreme temperature response function is insignificantly positive when we assume that *SALES_TA* is generated by randomizing the row order of the original *SALES_TA* observations. Fig. A4 shows that the depreciation expense to extreme temperature response function is insignificantly negative when we replace *SALES_TA* with the natural log of depreciation expense. Overall, these placebo tests support the logic and validity of our empirical design.

7.5 Other tests

Our main findings are qualitatively unchanged based on Poisson regression (assumes a non-negative dependent variable), extreme temperature spells defined as three consecutive days or more, public and private firms analyzed separately, and regressions with different combinations of fixed effects and ways to compute the standard errors of the regression coefficients.

8. Conclusion

We provide robust evidence that the response of financial performance to extreme high temperature spells is hump shaped or curvilinear, a result not documented in prior work. Specifically, financial performance improves for extreme temperature spells in normally cooler months or locations and worsens for spells in normally hotter months or locations. The hump shape of the sales-to-temperature response function also changes in predictable ways based on firm, sectoral, locational, and temporal characteristics. For example, the hump shape is more pronounced for EU/UK firms in low versus high latitudes, firms with more versus less geographic concentration of their operations, and firms in the non-energy and labor-intensive sectors. We also find that despite some variation due to time and place, the point at which financial performance changes from increasing to decreasing in spell maximum temperature is remarkably stable, around 23˚C for the sample as a whole. We find no evidence that the sales-to-temperature response function has changed over time or that firms' future ESG performance improves or emission levels decline after the extreme temperature spells, ostensibly as indicators of whether managers take actions in the future to mitigate the effects and the risks we document.

At a minimum, these findings, which are new to the literature, establish a baseline for future studies that follow our method and validation exercises. A limitation of our study is that we are unable to identify an exact mechanism to explain these findings. Nonetheless, we contend that the effects could have occurred in at least two ways. The first is that outdoor temperature extremes affect human traits such as apathy, mood, and sentiment, and the stress levels of employees and customers, even for those working or shopping in indoor environments. Consistent with this view, we find stronger extreme temperature spell impacts for firms in labor-intensive industries. The second relates to the direct effects of extreme temperature spells on business infrastructure and transportation. Such heat conditions may physically prevent operations or diminish workplace productivity or customer demand. Consistent with this second view, we find stronger results for firms in countries with less resilience to extreme heat, during the summer months when temperatures are already hotter on average, and for firms headquartered in low latitude EU countries, which are also already hotter on average.

Our findings imply an emerging tension. On the one hand, we show a marked effect of extreme temperature on sales and profits, supporting the view that extreme high temperature spell impacts should be disclosed if material. On the other hand, our analysis reveals no evidence that firms follow suit, as they do not improve their sustainability scores or reduce their carbon emissions after episodes of extreme temperature. One plausible explanation for this managerial passivity is a lack of awareness. Managers could be largely oblivious to the extreme weather phenomenon in their local context or may not have the expertise to ascertain and quantify its repercussions. Although the term extreme weather features prominently in disclosure guidance on physical climate risk by standard setters, without a well-recognized definition and comparable ways to measure the weather fallout of climate change, firms might continue to neglect this imperative. The existing literature, to the best of our understanding, falls short in offering practical guidance for firm managers on the risks and opportunities of extreme weather scenarios and ways to benchmark against their peers. Thus, for managers, what does not seem "extreme" need not require a response. Moreover, managers' non-disclosure or inaction does not equate to negligence; it might just be a difference of opinion on what is material financially. It is also conceivable that managers' views on what is an extreme temperature spell are subjectively determined based on their personal and business experiences and do not align well with the way our study defines extreme temperature, which is an outlier temperature substantially higher than what is in the normal or expected range of temperatures based on a reference period distribution conditional on time and place.

Despite managers' passivity, it is hoped that our evidence of deleterious effects might galvanize corporate leaders by showcasing findings that the previous literature and managers thus far might have overlooked. While, nowadays, the narrative and rhetorical discussion of climate change is becoming mainstream in corporate reporting, and sustainability disclosures have become more widespread and informative than before (e.g., SASB (2018) versus SASB (2023)), explicit definitions of extreme weather and methodologies to gauge the financial effects of the climate phenomenon are still needed.

In closing, the main message of our study for standard-setters and researchers is clear: It is imperative that they provide more guidance on extreme weather as it affects firms' resources and operations and offer methods to measure the fiscal implications of this climate anomaly. As a step toward improved disclosure, we encourage more research on this topic, particularly an analysis of the conditions, characteristics, and consequences for financial status and performance of spells of extreme high temperature in particular and extreme weather in general.

References

Addoum, J., D. Ng, and A. Ortiz-Bobea. 2020. Temperature shocks and establishment sales. *The Review of Financial Studies* 33 (3):1331-1366.

Addoum, J., D. Ng, and A. Ortiz-Bobea. 2023. Temperature shocks and industry earnings news. *Journal of Financial Economics* 150 (1):1-45.

Agnew, M. D., and J. E. Thornes. 1995. The weather sensitivity of the UK food retail and distribution industry. *Meteorological Applications* 2 (2):137-147.

Akhtar, R. 2020. Introduction: Extreme weather events and human health: A global perspective. In *Extreme Weather Events and Human Health: International Case Studies*, edited by R. Akhtar. Cham: Springer International Publishing, 3-11.
Alam, M. S., M. Atif, C. Chien-Chi, and U. Soytaş. 2019. Does corporate R&D investment affect firm environmental performance? Evidence from G-6 countries. *Energy Economics* 78:401-411.
Atlantic_Council. 2021. *Extreme heat: The economic and social consequences for the United States*. Adrienne-Arsht Rockefeller Foundation Resilience Center. August. https://www.atlanticcouncil.org/wp-content/uploads/2021/08/Extreme-Heat-Report-2021.pdf.
Badorf, F., and K. Hoberg. 2020. The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores. *Journal of Retailing and Consumer Services* 52:101921.
Barreca, A. I. 2012. Climate change, humidity, and mortality in the United States. *Journal of Environmental Economics and Management* 63 (1):19-34.
Baylis, P. 2020. Temperature and temperament: Evidence from Twitter. *Journal of Public Economics* 184:104161.
BIS. 2021. Climate-related risk drivers and their transmission channels. Basel Committee on Banking Supervision.Bank for International Settlements. https://www.bis.org/bcbs/publ/d517.pdf April.
Brooks, C., and L. Schopohl. 2021. Green accounting and finance: Advancing research on environmental disclosure, value ompacts and management control systems. *The British Accounting Review* 53:100973.
Burke, M., S. M. Hsiang, and E. Miguel. 2015. Global non-linear effect of temperature on economic production. *Nature* 527:235.
Busenbark, J. R., H. Yoon, D. L. Gamache, and M. C. Withers. 2021. Omitted variable bias: Examining management research with the impact threshold of a confounding variable (ITCV). *Journal of Management* 48 (1):17-48.
Cao, M., and J. Wei. 2005. Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance* 29 (6):1559-1573.
Chen, C., I. Noble, J. Hellman, J. Coffee, M. Murillo, and N. Chawla. 2015. University of Notre Dame *Global Adaptation Index Country Index* Technical Report, Unversity of Notre Dame, November.
Chen, X., and Z. Chen. 2021. Can green finance development reduce carbon emissions? Empirical evidence from 30 Chinese provinces. *Sustainability* 13 (21):12137.
Collins, S. N., R. S. James, P. Ray, K. Chen, A. Lassman, and J. Brownlee. 2013. *Grids in Numerical Weather and Climate Models*. DOI: 10.5772/55922. May.
Coonan, A. 2023. Heat waves scorch margins, employees, infrastructure: Business risks of extreme heat. Bradley Intelligence Report. https://www.bradley.com/insights/publications/2023/07/heat-waves-scorch-margins--employees-infrastructure-business-risks-of-extreme-heat August 1st.
Copernicus. 2023. *About Copernicus*. https://www.copernicus.eu/en/about-copernicus.
CSRD. 2021. Corporate Sustainability Reporting Directive (CSRD), issued by the European Financial Reporting Advisory Group (EFRAG). Directive 2013/34/EU, Directive 2004/109/EC, Directive 2006/43/EC and Regulation (EU) No 537/2014, as regards corporate sustainability reporting.
Dahl, K., E. Spanger-Siegfried, R. Licker, A. Caldas, J. Abatzoglou, N. Mailloux, R. Cleetus, S. Udvardy, J. Declet-Barreto, and P. Worth. 2019. Killer heat in the United States: Climate choices and the future of dangerously hot days, Union of Concerned Scientists.
de Villiers, C., V. Naiker, and C. J. van Staden. 2011. The effect of board characteristics on firm environmental performance. *Journal of Management* 37 (6):1636-1663.
DeGuindos, L. 2021. *Shining a light on climate risks: The ECB's economy-wideclimate stress test.* European Central Bank. March 18.
EU. 2022. Directive (EU) 2022/2464 of the European Pariliament and of the Council as regards corporate sustainability reporting. November 14.
———. 2023. European Commission green deal. Fit for 55 legislation. https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en October 9.
Floros, C. 2011. On the relationship between weather and stock market returns. *Studies in Economics and Finance* 28 (1):5-13.
Gregory, R., J. R. Lombard, and B. Seifert. 2005. Impact of headquarters relocation on the operating performance of the firm. *Economic Development Quarterly* 19 (3):260-270.

Hirshleifer, D., and T. Shumway. 2003. Good day sunshine: Stock returns and the weather. *The Journal of Finance* 58 (3):1009-1032.
Hoeppe, P. 2016. Trends in weather related disasters: Consequences for insurers and society. *Weather and Climate Extremes* 11:70-79.
IFRC. 2022. *Extreme heat: Preparing for the heatwaves of the future*. A joint publication of the United Nations Office for the Coordination of Humanitarian Affairs, the International Federation of Red Cross and Red Crescent Societies, and the Red Cross Red Crescent Climate Centre. October.
ILO. 2019. *Working on a warmer planet: The impact of heat stress on labour productivity and decent work*. International Labour Office – Geneva, ILO, 2019.
IPCC. 2021. *Climate change 2021: The physical science basis.* Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change https://www.ipcc.ch/report/ar6/wg1/#FullReport Cambridge University Press. August.
ISS. 2022. Carbon footprint dataset. Scope 1&2 and scope 3 emissions, including emission intensities. https://www.issgovernance.com/esg/climate-solutions/climate-analytics/.
ISSB_S1. 2023. General requirements for disclosure of sustainability-related financial information. IFRS sustainability disclosure standard. https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ June 26th.
ISSB_S2. 2023. Climate-related disclosures. IFRS sustainability disclosure standard. https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ June 26th.
Jin, Z., F. W. Li, Y. Lin, and Z. Zhang. 2021. Do firms adapt to rising temperatures? Evidence from Establishment-Level Data. Available at SSRN: https://ssrn.com/abstract=3573260 August 20th.
Kekäläinen, P., R. Niemelä, M. Tuomainen, S. Kemppilä, J. Palonen, H. Riuttala, E. Nykyri, O. Seppänen, and K. Reijula. 2010. Effect of reduced summer indoor temperature on symptoms, perceived work environment and productivity in office work. *Intelligent Buildings International* 2 (4):251-266.
Laamanen, T., T. Simula, and S. Torstila. 2012. Cross-border relocations of headquarters in Europe. *Journal of International Business Studies* 43 (2):187-210.
Larcker, D. F., and T. O. Rusticus. 2010. On the use of instrumental variables in accounting research. *Journal of Accounting and Economics* 49 (3):186-205.
Li, Z.-Z., R. Y. M. Li, M. Y. Malik, M. Murshed, Z. Khan, and M. Umar. 2021. Determinants of carbon emission in China: How good is green investment? *Sustainable Production and Consumption* 27:392-401.
Liu, J., B. M. Varghese, A. Hansen, Y. Zhang, T. Driscoll, and G. Morgan. 2022. Heat exposure and cardiovascular health outcomes: a systematic review and meta-analysis. *The Lancet Planetary Health* 6 (6):484-495.
Luo, X., P. Vahmani, T. Hong, and A. Jones. 2020. City-scale building anthropogenic heating during heat waves. *Atmosphere* 11 (11):1206.
Margaritis, D., and M. Psillaki. 2007. Capital structure and firm efficiency. *Journal of Business finance & accounting* 34 (9-10):1447-1469.
MetOffice, U. K. 2023. What is a heat wave? https://www.metoffice.gov.uk/weather/learn-about/weather/types-of-weather/temperature/heatwave.
Moody's. 2021. Critical industries have substantial exposure to physical climate risks. Moody's ESG Solutions. November.
Myers, S. C., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13 (2):187-221.
NGFS. 2019. Network for greening the financial system. *First comprehensive report. A call for action.* Climate change as a source of financial risk.1-38.
NOAA. 2020. GHCN (Global Historical Climatology Network)-Daily. National Oceanic and Atmospheric Administration. https://www.ncdc.noaa.gov/ghcn-daily-description.
Otto, F. E. L., S. Philip, S. Kew, S. Li, A. King, and H. Cullen. 2018. Attributing high-impact extreme events across timescales—a case study of four different types of events. *Climatic Change* 149 (3):399-412.
Pankratz, N., R. Bauer, and J. Derwall. 2023. Climate change, firm performance, and investor surprises. *Management Science* 69 (12).

Pedersen, L. H., S. Fitzgibbons, and L. Pomorski. 2021. Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics* 142 (2):572-597.
Rajan, R. G., and L. Zingales. 1995. What do we know about capital structure? Some evidence from international data. *The Journal of Finance* 50 (5):1421-1460.
Refinitiv. 2022. Environmental, social, and governance scores from Refinitive, May. https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf.
Russo, S., A. Dosio, R. G. Graversen, J. Sillmann, H. Carrao, M. B. Dunbar, A. Singleton, P. Montagna, P. Barbola, and J. V. Vogt. 2014. Magnitude of extreme heat waves in present climate and their projection in a warming world. *Journal of Geophysical Research: Atmospheres* 119 (22):12,500-512,512.
SASB. 2018. The state of disclosure 2017. An analysis of the effectiveness of sustainability disclosure in SEC filings https://sasb.org/wp-content/uploads/2019/08/StateofDisclosure-Report-web112717-1.pdf.
———. 2023. Companies reporting with SASB Standards. https://sasb.org/company-use/sasb-reporters/.
SB-253. 2023. Climate corporate data accountability act. https://leginfo.legislature.ca.gov/faces/billHistoryClient.xhtml?bill_id=202320240SB253. Signed into law, October 7.
Schlenker, W., and M. Roberts. 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc Natl Acad Science* 106 (37):15594-15598.
SEC. 2022. Proposed rule. *The Enhancement and Standardization of Climate-Related Disclosures for Investors.* Release Nos. 33-11042; 34-94478; File No. S7-10-22. Securities and Exchange Commission, Washington, DC. March 21st.
———. 2024. Final Rule. *The Enhancement and Standardization of Climate-Related Disclosures for Investors*. Release Nos. 33-11275; 34-99678; File No. S7-10-22. Securities and Exchange Commission, Washington, DC. March 6th.
Seppanen, O., W. Fisk, and Q. H. Lei. 2006. *Effect of temperature on task performance in office environment*. Lawrence Berkeley National Laboratory, Indoor Environment Department. July.
Swerling, G., and M. Murphy. 2022. Give workers tne day off if it's too hot, bosses told. *The Sunday Telegraph*. July 17th.
TFCD. 2017. Final report: Recommendations of the task force on climate related financial disclosures. June.
Walls, J. L., P. Berrone, and P. H. Phan. 2012. Corporate governance and environmental performance: is there really a link? *Strategic Management Journal* 33 (8):885-913.
Whelan, T., U. Atz, T. VanHolt, and C. Clark. 2021. ESG and financial performance: Uncovering the relationship by aggregating evidence from 1,000 plus studies published between 2015 – 2020. Research paper. NTU Stern Center for Sustainable Business.
Zanocco, C., H. Boudet, R. Nilson, H. Satein, H. Whitley, and J. Flora. 2018. Place, proximity, and perceived harm: Extreme weather events and views about climate change. *Climatic Change* 149 (3):349-365.
Zhang, Y., and D. T. Shindell. 2021. Costs from labor losses due to extreme heat in the USA attributable to climate change. *Climatic Change* 164 (3):35.
Zhao, M., J. K. W. Lee, T. Kjellstrom, and W. Cai. 2021. Assessment of the economic impact of heat-related labor productivity loss: A systematic review. *Climatic Change* 167 (1):22.
Zheng, J., M. U. Khurram, and L. Chen. 2022. Can green innovation affect ESG ratings and financial performance? Evidence from Chinese GEM listed companies. *Sustainability* 14 (14):8677.
Zivin, J., and M. Neidell. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics* 32 (1):1-26.
Zwebner, Y., L. Lee, and J. Goldenberg. 2014. The temperature premium: Warm temperatures increase product valuation. *Journal of Consumer Psychology* 24 (2):251-259.

Appendix A: Definition and interpretation of extreme high temperature spell

Although there is no universal consensus on what defines an extreme high temperature spell, researchers' and agencies' (e.g., NOAA, Copernicus, U.K. Met Office) definitions all include (i) a *threshold* based on a *reference period* (e.g., the temperature at the 95th-tile of the reference period distribution) and (ii) a *number of days* (usually two or three consecutive days) during which the temperature exceeds the threshold. Within the duration of an extreme temperature spell, there will also be a maximum temperature. For example, the UK Met Office (MetOffice 2023) requires a threshold of between 25˚C and 28˚C depending on location. So, if one were to observe five consecutive days of, say, 29˚C, 30˚C, 32˚C, 31˚C, and 29˚C in a 28˚C threshold location, the maximum or extreme temperature of this five-day extreme temperature spell would be 32˚C. Thus, even though the threshold is 28˚C, for this one extreme temperature spell, the temperature variable in this study – *SPELL_MAX_TEMP* – would be 32˚C.

Not all extreme temperature spells occur in the hottest months, however. This is because a reference period varies by time and place. The reference period for a northern latitude country in winter (e.g., Sweden) would be very different from that for a southern latitude country (e.g., Spain) in summer. Thus, following the approach of our paper, the average *SPELL_MAX_TEMP* for extreme temperature spells in Sweden in winter (the sample mean for January to March is 12.22˚C) would be much lower than the average *SPELL_MAX_TEMP* for extreme temperature spells in Spain in summer (the sample mean for July to August is 30.97˚C). Yet, they both represent extreme temperature spell maximums. As a specific example, the UK experienced a record-breaking winter extreme temperature spell in February 2019, which in London was 10˚C above the average normal February temperature of 9˚C (https://www.carbonbrief.org/media-reaction-uks-record-breaking-winter-heat-in-2019/). Our sample covers extreme temperature spells that occurred in all months of a year, including the UK winter heat spell of 2019.

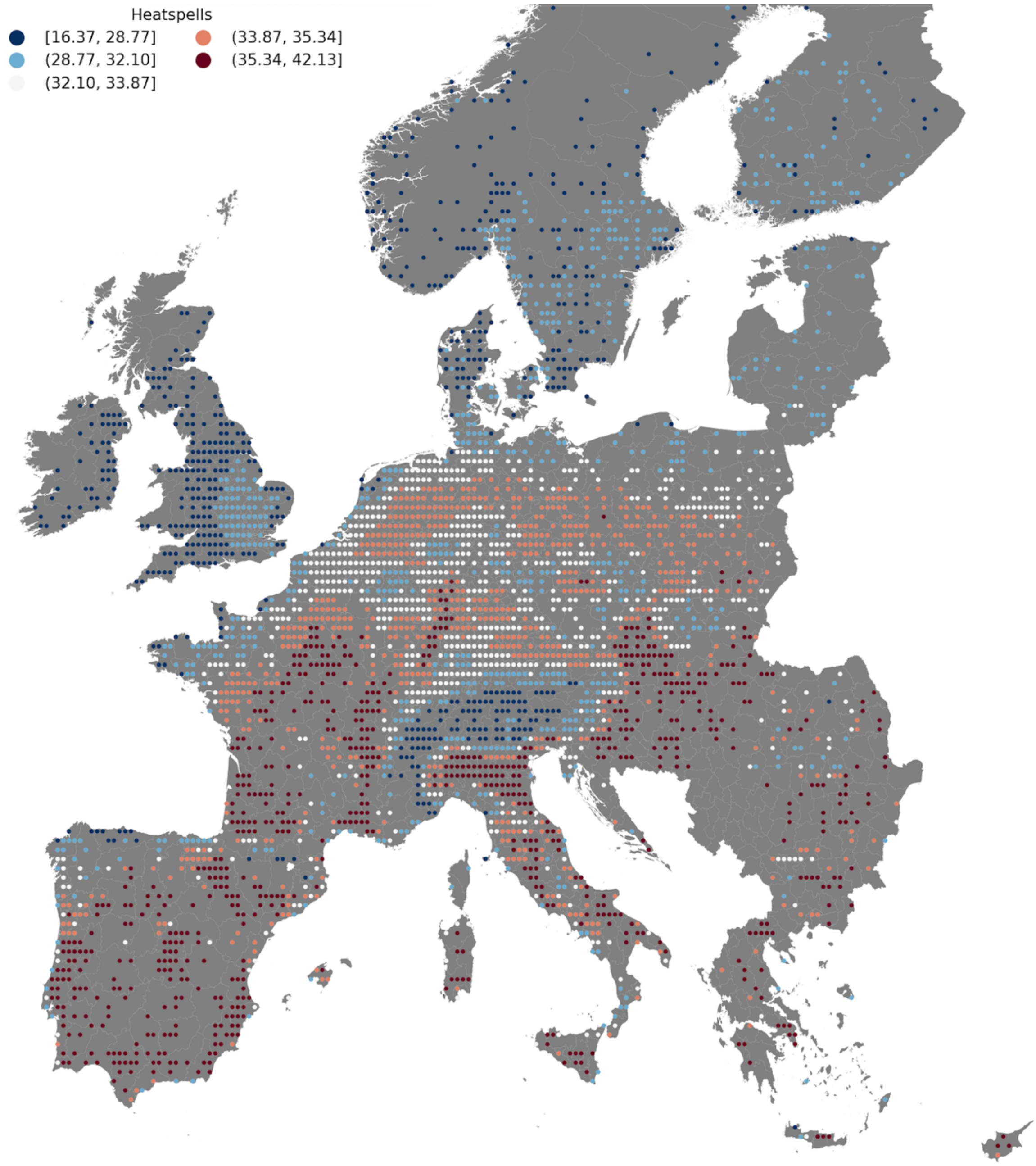
While we apply the definition of extreme temperature spell consistently in our analysis, *how one interprets SPELL_MAX_TEMP* could vary depending on the reference period assumed by a reader. For example, a UK reader could anchor on their personal location and business experience and might not consider *SPELL_MAX_TEMP* = 23˚C as an extreme temperature, possibly because the UK Met Office uses a threshold of 25˚C to 28˚C to define an extreme temperature in the United Kingdom (MetOffice 2023). A reader might also anchor on their experience with the temperature level itself and, thus, they might not consider *SPELL_MAX_TEMP* = 23˚C as extreme but rather as exceptional or abnormal, even though it is extreme as defined by the threshold based on the distribution of the reference period.

In short, it is important to view *SPELL_MAX_TEMP* as representing variation inherent in a wide range of maximum spell temperatures, which are extreme by reference to what is statistically well outside the range of normal temperature by time and place. To view *SPELL_MAX_TEMP* in terms of a fixed location or from the perspective of summer months only, runs the risk of misinterpreting the findings of this study.

Appendix B: Variable definitions

Variable	*Continuous or Indicator*	*Definition*
ΔEMISSIONS	C	Change in firm *i*'s Institutional Shareholder Services (ISS) Scope 1, 2, and 3 emissions from year *t-1* to *t*+3.
ΔESG_SCORE	C	Change in firm *i*'s Refinitiv ESG score from year *t*-1 to *t*+3.
DURATION	C	Sum of all extreme high temperature spell days (*SPELL_LENGTH*) in year *t* for firm *i*.
LEVERAGE	C	One minus the ratio of book equity-to-total assets for firm *i* at end of year *t*.
NI_SALES	C	Pretax profit-to-sales ratio for firm i for year *t*.
NUTSX_MAX_TEMP	C	Average *SPELL_MAX_TEMP* in *NUTS1* or *NUTS2* region in year *t*.
ROA	C	Pretax profit-to-total assets at beginning of year *t* ratio for firm *i*.
SALES_TA	C	Sales for year *t* divided by total assets (*TA*) at start of year *t*.
SPELL_LENGTH	C	Length in days of an individual *HEAT_SPELL* in year *t* affecting firm *i*.
SPELL_MAX_TEMP	C	Average maximum spell temperature (in Celsius) of individual extreme temperature spells (*SPELL_TEMP*) in year *t* for firm *i*.
WHOLESALE_RETAIL	C	Retail and wholesale sales in each country of location in year *t* scaled by average total assets for firms in each country at start of year *t*.
DISTANT	I	1 = Firm *i* headquarters is located within 100 km of any one of the 26 capital cities of EU and UK, otherwise 0 (*CLOSE*).
DUM_CRITICAL	I	1 = if the average *SPELL_MAX_TEMP* is higher than the median of average *SPELL_MAX_TEMP* in a year, otherwise 0.
ENERGY	I	1 = Firm *i* in year *t* is in the Global Industry Classification Standard energy sector, otherwise 0.
GROUP_SIZE	I	1 = the number of subsidiaries in the group (consolidated entity) is greater than the sample median by year, otherwise 0.
LABOR-INTENSIVE	I	1 = Firm *i* is in consumer discretionary (consumer durables, restaurants, hotels, and leisure), materials, or real estate sectors, otherwise 0.
LATITUDE	I	Extreme temperature spell occurs in the same latitude of firm *i*'s headquarters split into quintiles = 1 for Quintile 1 (Low Latitude location) or 0 for Quintile 5 = (High Latitude location).
SEASON	I	1 = Extreme temperature spells in year *t* on average occur in the summer months of year *t* (July, August, and September), otherwise 0.
SPELL_TEMP	I	Indicates that the maximum daily temperature of a spell in the same location as firm *i*'s headquarters exceeds the 95-percentile based on the distribution of the previous five years of daily temperatures in the same location and season for at least two consecutive days.
UK.FR.DE	I	1 = Firm *i* is headquartered in the United Kingdom, France, or Germany, otherwise 0.
VULNERABLE	I	1 = Firm *i* is headquartered in a high climate-change vulnerable country, otherwise a non-climate-change vulnerable country (0). The split is at the median by year of the EU countries in the Notre Dame *ND GAIN* index (Chen et al. 2015).
WEEKDAY	I	1 = The individual spell temperature (*SPELL_TEMP*) for firm *i* in year *t* on average occurs on a weekday, otherwise 0.

Fig. 1. Distribution of UK and European extreme temperature spells in summers of 2011–2019



This figure maps the distribution of the extreme high temperature spells in the UK and Europe for the summers (Jul-Aug-Sep) of 2011–2019. An extreme high temperature spell occurs when the temperature exceeds the 95th percentile over the last five years for a given season for two consecutive days or more. The light grey surrounds represent a *NUTS2* region. The legend shows that the hottest summer extreme temperature spells (dark red), with temperatures of 35.34˚C to 42.13˚C, occur mostly in the southern latitude or eastern countries, whereas the coolest summer extreme temperature spells (dark blue = 16.37˚C to 28.77˚C) occur mostly in Scandinavia, the western UK, and Ireland. The white dots show temperatures between 32.10˚C and 33.87˚C.

Fig. 2. The hump-shaped sales-to-temperature response function

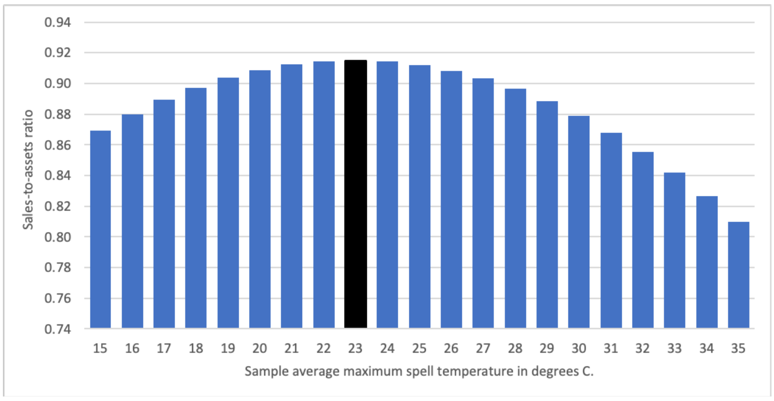


Fig. 2.1. This graph, based on Eq. (1), plots the sample-wide sales-to-assets ratio for different levels of extreme temperature spell. The sales-to-assets ratio begins to decline for maximum spell temperatures exceeding 23˚C (shown in black).

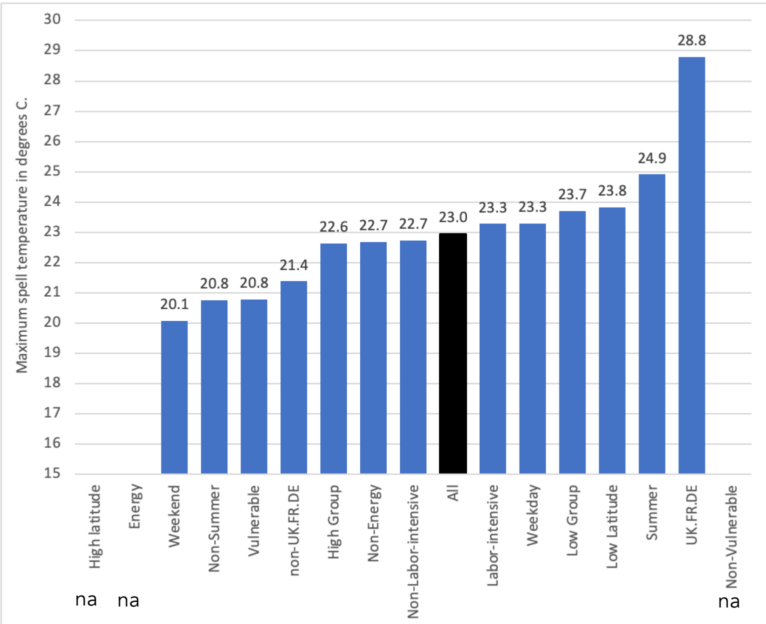


Fig. 2.2. This graph, based on Eq. (1), plots the maximum sales-to-assets ratio after which it begins to decline for different partitions of the sample. For firms in high latitudes, the energy sector, and firms in countries ranked low in vulnerability to climate change (non-vulnerable), the sales-to-assets ratio does not decline in the relevant temperature range of 15˚C to 30 ˚C.

Fig. 3. The effect of extreme temperature spell duration on the sales-to-temperature response function

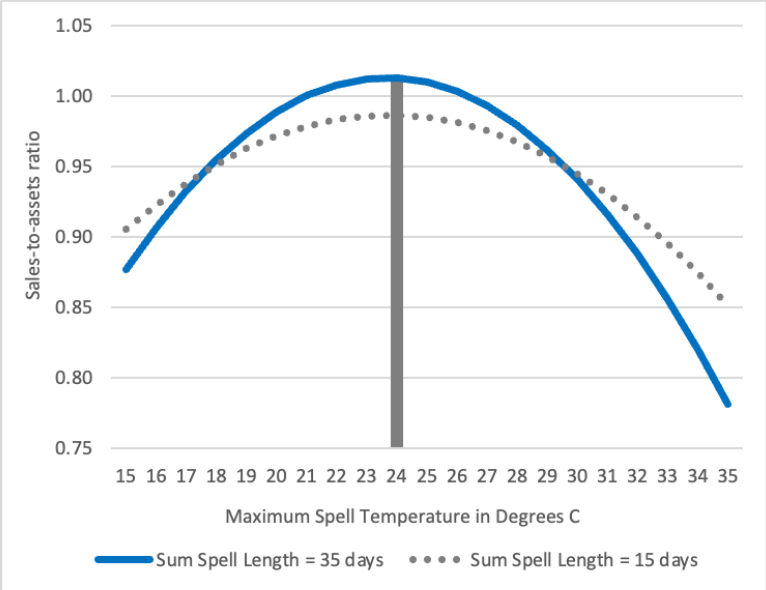


Fig. 3.1. This graph plots the sales-to-temperature response function based on Eq. (2) for the full sample for extreme temperature spells of shorter (*DURATION* = 15 days) versus longer duration (*DURATION* = 35 days). The maximum spell temperature after which sales begin to decline (grey column) is approximately the same for longer and shorter extreme temperature spells. For longer duration spells (the blue curve) the falloff in sales occurs at a steeper rate than for shorter duration spells (the dotted curve).

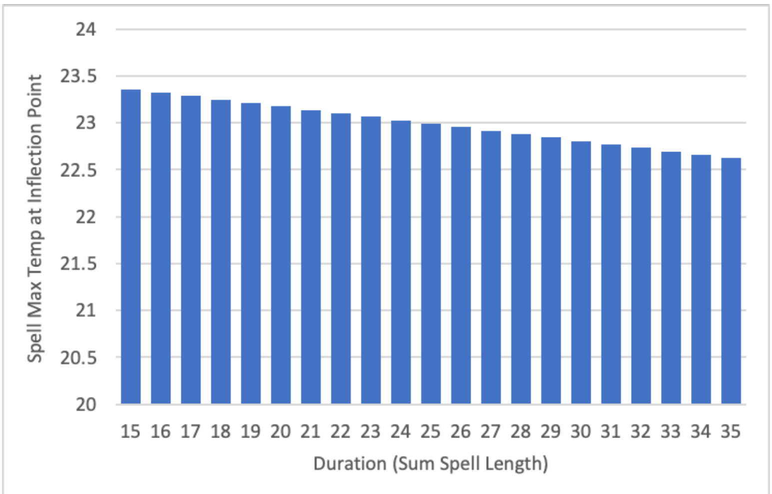


Fig. 3.2. This graph plots that the maximum spell temperature after which sales begin to decline for the full sample is slightly higher for maximum temperature spells of shorter (*DURATION* = 15 days) versus longer duration (*DURATION* = 35 days).

Fig. 4. The effect of extreme spell temperature and duration on pretax profit margin

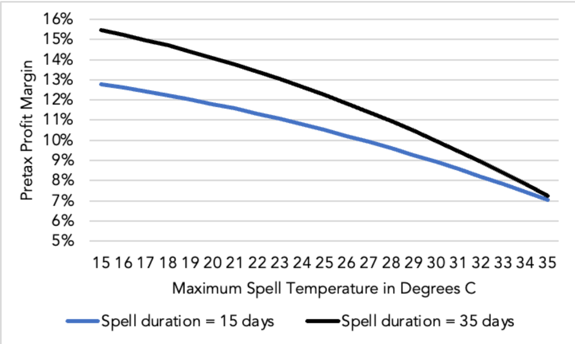


Fig. 4.1. Full sample

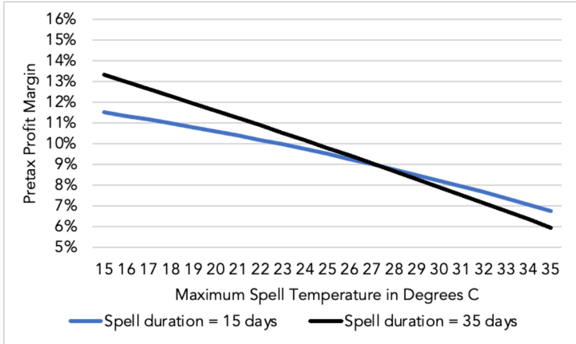


Fig. 4.3 Distant from Major City

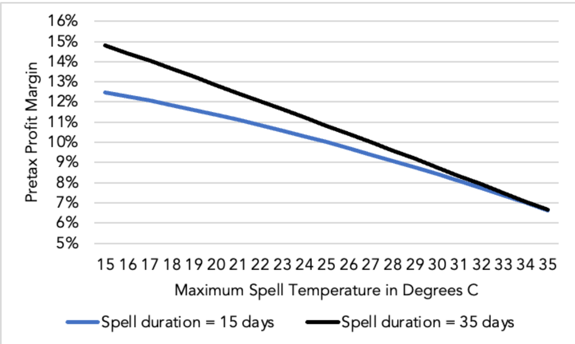


Fig. 4.2. Low Group Size

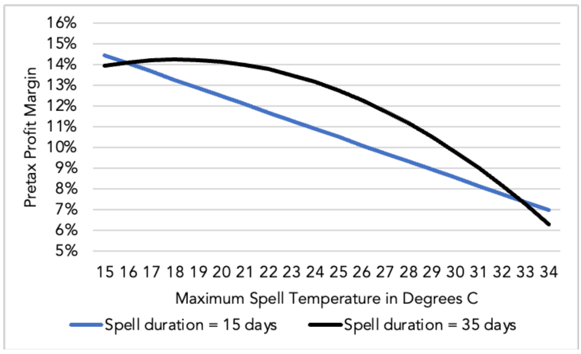


Fig 4.4. Summer months

These graphs plot the response of pretax profit margin to extreme high temperature spells for extreme temperature spells of short duration (blue curve) and long duration (black curve). The plots are based on the coefficients for Eq. (2) for the full sample applied to pretax profit margin. Overall, pretax profit margin (*NI_SALES*) declines as the extreme temperature of a spell (*SPELL_MAX_TEMP*) increases (Figs. 4.1–4.4). Based on Fig. 4.1, if the maximum spell temperature were to exceed the sample-wide average of 23˚C by 5˚C, the pretax profit margin would decrease by 12.9 percent for *DURATION* of 15 days.

Fig. 5. The effect of extreme spell temperature and duration on pretax ROA

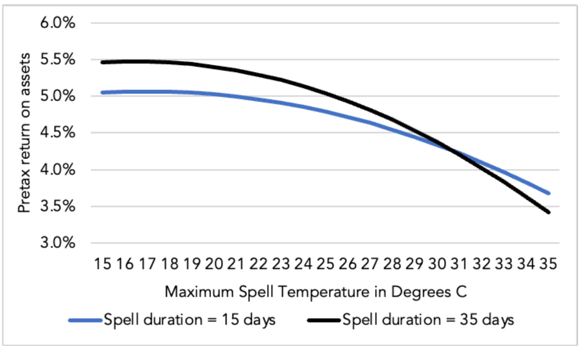


Fig. 5.1. Full sample

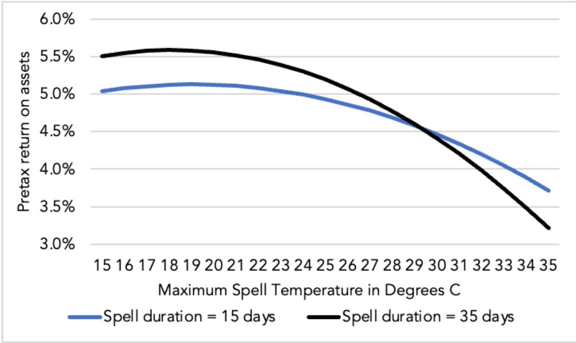


Fig. 5.3. Distant from Major City

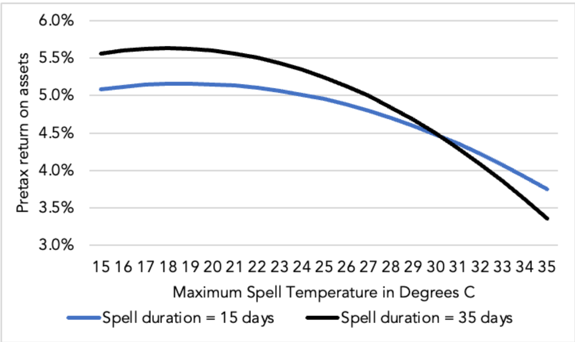


Fig. 5.2. Low Group Size

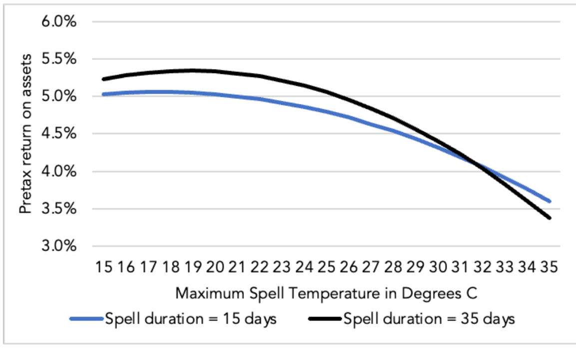
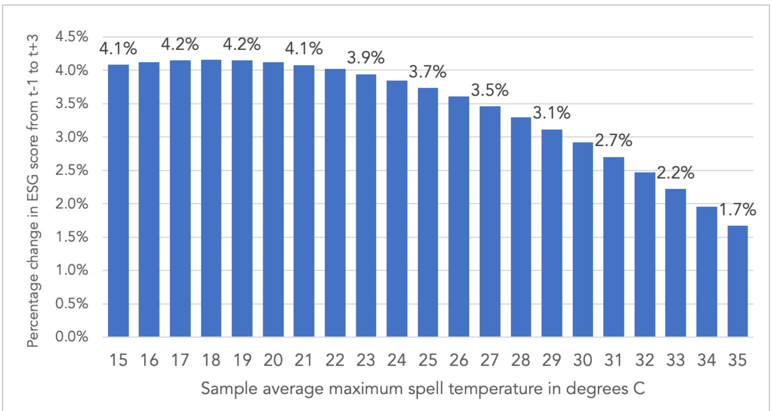


Fig 5.4. Summer months

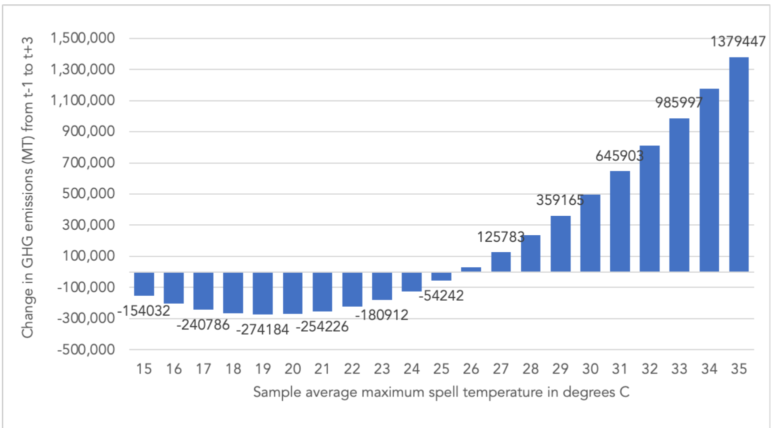
These graphs plot the response of pretax ROA to extreme temperature spells for spells of short duration (blue curve) and long duration (black curve). The plots are based on the coefficients for Eq. (2) for the full sample applied to pretax ROA. Based on Fig. 5.1, if the maximum spell temperature were to exceed the sample-wide average of 23˚C by 5˚C, the pretax ROA would decrease by 7.7 percent for *DURATION* of 15 days.

Fig. 6. The effect of extreme high temperature spells on ESG performance



This graph plots the sample-wide change in firms' ESG score from year *t*-1 to *t*+3 (year *t* is the year of the spell) for different levels of extreme spell temperature based on the coefficients for Regr. 1 of Table 7. The plot shows that the growth in ESG score becomes smaller as the maximum spell temperature increases.

Fig. 7. The effect of extreme high temperature spells on carbon emissions



This graph plots the sample-wide change in Scope 1, 2, and 3 emissions in metric tons (MT) from year *t*-1 to *t*+3 (year *t* is the year of the extreme temperature spell) for different levels of extreme high temperature spells based on the coefficients for Regr. 1 of Table 8. The columns to the left show that emissions decrease for extreme high temperature spells in normally cooler conditions (with *SPELL_MAX_TEMP* within 15˚C to 25˚C). The columns to the right show that emissions increase for extreme high temperature spells in normally hotter conditions (with *SPELL_MAX_TEMP* of 26˚C or more).

Table 1. Sample descriptive characteristics

Variable		*SALES_TA*				*NI_SALES*				*LEVERAGE*				*SPELL_MAX_TEMP*				*DURATION*			
Statistic	N obs. (max.)	Mean	Std. Dev.	Q.10	Q.90	Mean	Std. Dev.	Q.10	Q.90	Mean	Std. Dev.	Q.10	Q.90	Mean	Std. Dev.	Q.10	Q.90	Mean	Std. Dev.	Q.10	Q.90
Sector																					
Communication Services	11,462	1.11	0.90	0.17	2.37	0.06	0.21	-0.10	0.22	0.60	0.25	0.24	0.91	25.4	5.7	17.9	32.8	14.8	8.3	5.0	26.0
Consumer Discretionary	20,090	0.91	0.83	0.11	2.03	0.07	0.20	-0.07	0.26	0.52	0.27	0.10	0.87	25.6	5.4	18.5	32.6	15.4	8.2	5.0	26.0
Consumer Staples	19,168	1.00	1.04	0.14	2.57	0.11	0.21	-0.03	0.35	0.62	0.24	0.27	0.92	23.8	5.3	16.9	30.0	16.8	8.4	7.0	28.0
Energy	51,499	0.82	0.79	0.07	1.85	0.09	0.23	-0.06	0.34	0.59	0.27	0.19	0.92	25.4	5.1	18.4	31.4	16.8	8.5	7.0	29.0
Financials	76,871	0.67	0.82	0.03	1.73	0.11	0.26	-0.05	0.40	0.68	0.28	0.22	0.96	24.9	5.0	18.0	30.7	17.2	8.2	8.0	28.0
Health Care	38,937	0.57	0.69	0.06	1.49	0.20	0.29	-0.03	0.62	0.57	0.26	0.17	0.90	23.8	5.2	16.6	29.7	17.1	8.8	7.0	30.0
Industrials	101,791	0.91	0.80	0.09	1.94	0.09	0.22	-0.06	0.31	0.57	0.26	0.20	0.92	25.3	5.1	18.3	31.7	16.7	8.3	7.0	28.0
Information Technology	29,649	1.06	0.85	0.17	2.14	0.04	0.21	-0.11	0.20	0.53	0.25	0.19	0.87	25.4	5.6	18.3	32.4	14.9	8.5	5.0	26.0
Materials	48,038	0.96	0.84	0.08	2.07	0.11	0.26	-0.05	0.37	0.55	0.26	0.16	0.88	23.9	4.9	17.1	29.4	17.5	8.3	8.0	29.0
Real Estate	26,785	0.79	1.00	0.05	2.22	0.15	0.30	-0.06	0.59	0.56	0.27	0.14	0.91	25.5	5.3	18.4	32.2	16.6	8.3	7.0	27.0
Unassigned	79,257	0.93	0.89	0.06	2.12	0.11	0.25	-0.05	0.39	0.63	0.27	0.22	0.96	25.5	4.6	19.1	30.8	16.9	7.5	7.0	28.0
Utilities	55,530	0.97	0.98	0.05	2.33	0.11	0.27	-0.06	0.43	0.59	0.28	0.15	0.93	25.4	5.3	18.3	32.2	17.0	8.1	8.0	28.0
All	559,077	0.87	0.87	0.06	2.02	0.10	0.25	-0.06	0.39	0.59	0.27	0.19	0.93	25.0	5.1	17.9	31.2	16.8	8.2	7.0	28.0
Energy v. Other Firms																					
Non-Energy	507,578	0.87	0.87	0.06	2.04	0.11	0.25	-0.06	0.39	0.59	0.27	0.19	0.93	25.0	5.1	17.9	31.2	16.7	8.2	7.0	28.0
Energy	51,499	0.82	0.79	0.07	1.85	0.09	0.23	-0.06	0.34	0.59	0.27	0.19	0.92	25.4	5.1	18.4	31.4	16.8	8.5	7.0	29.0
Labor intensive v. Other Firms																					
Labor intensive	133,850	0.80	0.85	0.06	1.93	0.14	0.27	-0.05	0.50	0.55	0.27	0.15	0.89	24.4	5.2	17.3	30.5	16.9	8.5	7.0	28.0
Non-Labor intensive	425,227	0.89	0.87	0.06	2.05	0.09	0.24	-0.06	0.34	0.61	0.27	0.20	0.94	25.2	5.1	18.3	31.4	16.7	8.2	7.0	28.0
Countries																					
GB, FR, and DE	216,953	0.91	0.89	0.06	2.09	0.11	0.26	-0.05	0.42	0.59	0.27	0.19	0.94	24.9	4.2	19.1	29.9	16.9	7.9	7.0	27.0
Other EU	342,124	0.84	0.85	0.06	1.97	0.10	0.24	-0.06	0.37	0.59	0.27	0.19	0.93	25.2	5.8	17.2	32.2	16.6	8.5	7.0	28.0
Latitude																					
Low (Quintile1)	111,154	0.77	0.76	0.06	1.72	0.08	0.24	-0.08	0.33	0.61	0.26	0.22	0.92	28.7	4.9	22.7	34.6	16.0	8.3	6.0	26.0
High (Quintile5)	102,229	0.87	0.89	0.07	2.09	0.12	0.25	-0.05	0.43	0.59	0.27	0.17	0.93	19.9	4.9	13.0	26.0	16.1	10.0	4.0	31.0
Day																					
Weekday	380,972	0.89	0.87	0.06	2.04	0.10	0.24	-0.05	0.37	0.60	0.27	0.20	0.93	24.8	5.2	17.6	31.1	17.3	8.1	8.0	28.0
Weekend	103,737	0.85	0.86	0.05	2.01	0.11	0.27	-0.06	0.43	0.58	0.27	0.17	0.93	25.8	4.7	20.5	32.0	14.8	8.4	5.0	26.0
Season																					
Not Summer	194,452	0.89	0.86	0.06	2.03	0.10	0.24	-0.05	0.36	0.59	0.27	0.19	0.92	23.6	5.4	16.4	29.6	14.7	7.3	5.0	24.0
Summer (Jul-Aug-Sep)	290,257	0.88	0.87	0.06	2.04	0.11	0.25	-0.05	0.39	0.60	0.27	0.20	0.93	26.0	4.7	19.9	32.0	18.2	8.5	8.0	31.0
Number of Subsidiaries																					
Low	188,230	0.89	0.86	0.07	2.02	0.10	0.23	-0.04	0.36	0.64	0.25	0.27	0.95	24.9	5.1	17.9	30.9	17.4	8.2	8.0	29.0
High	219,322	0.95	0.94	0.05	2.24	0.12	0.26	-0.04	0.44	0.56	0.28	0.14	0.92	24.8	4.9	17.9	30.5	17.5	8.1	8.0	29.0
ND Gain Index																					
Non-vulnerable country	267,069	0.90	0.89	0.06	2.10	0.12	0.27	-0.05	0.45	0.58	0.27	0.17	0.93	24.1	4.6	17.9	29.0	16.7	8.1	7.0	27.0
Vulnerable Country	287,092	0.85	0.84	0.06	1.95	0.09	0.23	-0.06	0.34	0.60	0.27	0.20	0.93	26.1	5.5	18.4	32.9	16.9	8.4	7.0	28.0

This table summarizes the dependent variables and covariates in Eq. (1). These are *SALES_TA*, *NI_SALES*, *LEVERAGE*, the average annual maximum spell temperature (*SPELL_MAX_TEMP*), and the annual sum of spell lengths in days (*DURATION*). Financial firm revenue (part of the financial sector) is defined as interest income. Labor intensive = consumer discretionary (incl. consumer durables, restaurants, hotels, and leisure), materials, and real estate sectors. Vulnerable = 1 if the firm locates in a high climate-change vulnerable country, otherwise a non-climate-change vulnerable country. The split is at the median by year of the EU countries in the Notre Dame *ND GAIN* index (Chen et al. 2015). The number of observations in the regression tables is less than N obs. (max.) due to missing observations for one or more variables.

Table 2. Correlations among the variables

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	*SALES_TA*	1.000	**-0.234**	0.096	0.010	0.002	-0.017	-0.044	0.039	0.063	0.018	-0.007	0.038	-0.001
2	*NI_SALES*	**-0.324**	1.000	**-0.109**	-0.074	0.039	-0.015	0.077	0.030	0.077	-0.021	0.013	0.055	0.055
3	*LEVERAGE*	0.007	-0.148	1.000	0.007	0.024	-0.008	-0.083	-0.011	-0.038	0.020	0.022	**-0.145**	-0.015
4	*SPELL_MAX_TEMP*	0.034	-0.076	0.006	1.000	0.018	0.024	-0.069	-0.029	**-0.666**	-0.077	**0.231**	-0.006	-0.029
5	*DURATION*	-0.005	0.033	0.026	0.002	1.000	0.003	0.009	0.015	0.005	0.121	**0.208**	0.010	-0.001
6	*ENERGY-SECTOR*	-0.002	-0.001	-0.009	0.028	0.003	1.000	**-0.179**	-0.116	0.024	0.001	0.004	-0.063	-0.056
7	*LABOR-INTENSIVE*	-0.055	0.086	-0.087	-0.071	0.003	**-0.179**	1.000	0.045	**0.126**	-0.021	-0.006	0.007	-0.012
8	*UK.FR.DE*	0.036	0.008	-0.011	-0.059	0.016	-0.116	0.045	1.000	**0.127**	-0.029	0.055	0.096	**0.555**
9	*HIGH_LATITUDE*	0.034	**0.106**	-0.033	**-0.686**	-0.031	0.024	**0.126**	**0.127**	1.000	0.048	-0.022	0.039	0.032
10	*WEEKDAY*	0.025	-0.013	0.018	-0.064	**0.149**	0.001	-0.021	-0.029	0.048	1.000	-0.001	-0.005	-0.019
11	*SUMMER*	-0.013	0.001	0.024	**0.218**	**0.191**	0.004	-0.006	0.055	-0.022	-0.001	1.000	0.010	0.074
12	*HIGH GROUP_SIZE*	0.017	0.033	**-0.137**	-0.009	0.011	-0.063	0.007	0.096	0.039	-0.005	0.010	1.000	0.042
13	*NON-VULNERABLE*	0.000	0.049	-0.026	-0.210	0.012	**-0.106**	0.081	**0.625**	0.039	0.007	0.058	0.059	1.000

This table summarizes the correlations among the variables in Eq. (1) (continuous variables 1 to 5) and the partitions of the sample (indicator variables 6 to 13). The upper diagonal shows the Pearson correlations. The lower diagonal shows the Spearman rank correlations. The number of observations for each correlation calculation depends on the number of sample observations for each variable. Correlations greater than +/-0.10 are shown in bold.

Table 3. Response of the sales-to-assets ratio to extreme high temperature spells

	Coeff.	t-stat.	Sig.	Coeff.	t-stat.	Sig.	Coeff.	t-stat.	Sig.	Coeff.	t-stat.	Sig.	Coeff.	t-stat.	Sig.
Panel A	1.All			2.Energy			3.Labor-intensive			4.UK.DR.DE			5.Low Latitude		
SPELL_MAX_TEMP	0.0333	4.83	***	-0.0011	-0.08		0.0517	6.49	***	0.0341	1.56		0.0132	2.51	**
SPELL_MAX_TEMP^2	-0.0007	-5.15	***	0.0001	0.41		-0.0011	-6.68	***	-0.0006	-1.34		-0.0003	-2.74	***
DURATION	0.0003	0.79		-0.0002	0.89		0.0011	0.21		0.0022	0.83		-0.0006	0.16	
LEVERAGE	0.3744	15.10	***	0.5031	10.96	***	0.5369	18.11	***	0.4223	15.24	***	0.3358	13.33	***
CONSTANT	0.2976	4.13	***	0.4919	2.97	***	-0.0693	-0.74		0.1781	0.67		0.4515	6.58	***
R Square Adj.	4.53%			0.0286			7.64%			5.91%			2.78%		
Observations	328,610			32,081			99,025			115,201			77,070		
Panel B				6.Non-Energy			7.Non-Labor-intensive			8.Non-UK.DR.DE			9.High Latitude		
SPELL_MAX_TEMP				0.0367	5.10	***	0.0259	3.26	***	0.0306	3.47	***	-0.0008	-0.17	
SPELL_MAX_TEMP^2				-0.0008	-5.42	***	-0.0006	-3.58	***	-0.0007	-4.20	***	0.0002	1.71	*
DURATION				0.0004	0.75		0.00003	0.99		0.0008	0.43		-0.0013	0.02	**
LEVERAGE				0.3609	14.41	***	0.3053	11.08	***	0.3433	11.82	***	0.3621	10.40	***
CONSTANT				0.2791	3.75	***	0.4519	5.48	***	0.3638	3.41	***	0.6382	12.58	***
R Square Adj.				4.69%			3.05%			4.84%			1.99%		
Observations				296,529			229,585			213,409			55,297		
Tests of differences															
SPELL_MAX_TEMP (A-B)				-0.0379	-3.05	***	0.0258	3.77	***	0.0035	-0.25		0.0141	-0.82	
SPELL_MAX_TEMP^2 *(A-B)*				0.0009	3.52	***	-0.0005	-3.85	***	0.0001	0.63		-0.0005	1.42	
Panel C	1.All			10.Weekday			11.Non-Summer			12.Low Subs. in Group			13.Vulnerable		
SPELL_MAX_TEMP	0.0333	4.83	***	0.0365	5.65	***	0.0264	3.31	***	0.0486	4.94	***	0.0284	3.31	***
SPELL_MAX_TEMP^2	-0.0007	-5.15	***	-0.0008	-5.60	***	-0.0006	-3.82	***	-0.0010	-5.05	***	-0.0007	-4.11	***
DURATION	0.0003	0.79		-0.0002	0.89		0.0011	0.21		0.0022	0.83		-0.0006	0.16	
LEVERAGE	0.3744	15.10	***	0.3692	14.43	***	0.3810	14.17	***	-0.2206	-5.47	***	0.3174	9.51	***
CONSTANT	0.2976	4.13	***	0.2608	3.48	***	0.4070	4.38	***	0.5395	4.46	***	0.4043	4.21	***
R Square Adj.	4.53%			4.67%			5.12%			4.43%			5.97%		
Observations	328,610			255,004			135,304			108,111			169,349		
Panel D				14.Weekend			15.Summer			16.High Subs. in Group			17.Non-Vulnerable		
SPELL_MAX_TEMP				0.0190	1.18		0.0490	5.47	***	0.0146	1.53		0.0122	1.89	*
SPELL_MAX_TEMP^2				-0.0005	-1.54		-0.0010	-5.21	***	-0.0003	-1.63		-0.0001	-0.83	
DURATION				-0.0013	0.31		0.0009	0.54		-0.0002	0.92	***	0.0004	0.80	
LEVERAGE				0.3862	13.79	***	0.3700	12.71	***	0.8738	24.98	***	0.4413	17.97	***
CONSTANT				0.4937	2.44	**	0.0572	0.61		0.2928	3.12	**	0.4287	7.36	***
R Square Adj.				0.0502			4.30%			7.79%			5.46%		
Observations				73,606			193,306			50,080			157,704		
Tests of differences															
SPELL_MAX_TEMP (C-D)				0.0174	1.05		-0.0226	1.78	*	0.0340	-3.92	***	0.0161	2.07	*
SPELL_MAX_TEMP^2 *(C-D)*				-0.0003	-0.98		0.0003	-1.12		-0.0007	4.28	***	-0.0005	-3.22	***

This table summarizes the coefficients for Eq. (1) stated as $SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon$ for the full sample and partitions of the full sample. The regressions control for year and sector fixed effects to adjust for unrelated time trends and sector differences. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

Table 4. Response of the pretax net profit-to-sales ratio to extreme high temperature spells

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A	1.All			2.Energy			3.Labor-Intensive			4.UK.DR.DE			5.Low Latitude		
SPELL_MAX_TEMP	0.0001	0.09		0.0071	1.38		0.0012	0.48		-0.00074	-0.09		0.0074	2.71	**
SPELL_MAX_TEMP^2	-0.00006	-2.05	*	-0.0002	-2.45	**	-0.0001	-1.70		-0.00009	-0.55		-0.0003	-2.75	**
DURATION	0.0008	3.35	***	0.0009	1.87	*	0.0007	2.41		0.0013	1.34		0.0012	4.94	***
LEVERAGE	-0.0936	-13.98	***	-0.0935	-7.02	***	-0.0847	-8.12	***	-0.0979	-10.30	***	0.3358	-17.24	***
CONSTANT	0.1830	7.64	***	0.1202	1.79	*	0.2006	6.07	***	0.2326	2.09	*	0.4515	2.09	*
Year and Sector Fixed Effects	Yes			Yes			Yes			Yes			Yes		
R Square Adj.	4.77%			2.79%			4.99%			6.92%			2.78%		
Observations	294,827			30,276			93,056			101,997			77,070		
Panel B				6.Non-Energy			7.Non-Labor-Intensive			8.Non-UK.DR.DE			9.High Latitude		
SPELL_MAX_TEMP				-0.0006	-0.42		-0.0002	-0.16		-0.00356	-2.62	**	0.0026	0.77	
SPELL_MAX_TEMP^2				0.0000	-1.46		-0.0001	-1.85	*	0.00004	1.43		-0.0001	-1.22	
DURATION				0.0008	3.62	***	0.0009	3.54	***	0.00053	2.06	*	0.0006	1.90	*
LEVERAGE				-0.0935	-13.95	***	-0.0977	-15.05	***	-0.08989	-13.34	***	-0.0518	-4.15	***
CONSTANT				0.1896	8.51	***	0.1739	7.24	***	0.20603	11.28	***	0.1415	4.73	***
R Square Adj.				4.99%			3.24%			4.55%			7.76%		
Observations				264,101			201,771			192,830			47,116		
Tests of differences															
SPELL_MAX_TEMP (A-B)				0.0077	1.46		0.0014	1.50		0.0028	1.03		0.0047	-0.550	
SPELL_MAX_TEMP^2 *(A-B)*				-0.0002	-1.95	*	0.0000	-1.65	*	-0.0001	-1.59		-0.0002	-0.350	
Panel C	All			10.Weekday			11.Non-Summer			12.Low Subs. in Group			13.Vulnerable		
SPELL_MAX_TEMP	0.0001	0.09		-0.0017	-1.06		-0.0009	-0.39		-0.0004	-0.28		-0.0062	-2.70	**
SPELL_MAX_TEMP^2	-0.00006	-2.05	*	-0.00003	-0.80		-0.00003	-0.60		-0.0001	-1.90	*	0.0001	2.20	**
DURATION	0.0008	3.35	***	0.0007	2.73	**	0.0005	1.10		0.0005	2.42	**	0.0005	2.49	**
LEVERAGE	-0.0936	-13.98	***	-0.0892	-13.33	***	-0.0878	-11.43	***	-0.0003	-0.04		-0.0819	-13.64	***
CONSTANT	0.1830	7.64	***	0.2036	9.31	***	0.1852	7.22	***	0.1351	7.20	***	0.2229	7.03	***
R Square Adj.	4.77%			4.81%			4.58%	0.00		3.84%			3.98%		
Observations	294,827			228,767			121,492	0.00		98,458			153,170		
Panel D				14.Weekend			15.Summer			16. High Subs. in Group			17.Non-Vulnerable		
SPELL_MAX_TEMP				0.0079	1.88	*	-0.0030	-0.87		0.0016	0.63		0.0074	2.97	***
SPELL_MAX_TEMP^2				-0.0002	-2.51	**	0.0000	-0.25		-0.0001	-1.92	*	-0.0002	-4.41	***
DURATION				0.0017	2.59	**	0.0007	1.99	*	0.0004	1.03		0.0009	1.48	
LEVERAGE				-0.1074	-9.90	***	-0.0971	-12.12	***	-0.1741	-15.78	***	-0.1010	-9.97	***
CONSTANT				0.0810	1.38		0.2415	4.81	***	0.2363	6.35	***	0.1278	3.97	***
R Square Adj.				5.69%			5.25%			6.41%			6.47%		
Observations				66,060			173,335			103,467			140,280		
Tests of differences															
SPELL_MAX_TEMP (C-D)				0.0002	-2.11	**	0.0000	-0.28		0.0000	1.05		0.0003	-5.520	***
SPELL_MAX_TEMP^2 *(C-D)*				-0.0010	1.95	*	-0.0002	-0.13		0.0000	-1.19		-0.0004	7.280	***

This table summarizes the coefficients for Eq. (1) stated as $NI\_SALES = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon$ for the full sample and partitions of the full sample. The regressions control for year and sector fixed effects to adjust for unrelated time trends and sector differences. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

Table 5. **Sales-to-assets ratio and extreme high temperature spells: Impact of duration**

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A	1.All			2.Energy			3.Labor-intensive			4.UK.FR.DE			5.Low Latitude		
SPELL_MAX_TEMP	0.0243	2.24	*	-0.0035	-0.17		0.035	2.27	*	0.0468	1.2		-0.0545	-3.73	***
SPELL_MAX_TEMP × *DURATION*	0.0018	3.17	**	0.0011	0.63		0.0029	2.75	**	-0.0047	-1.16		0.0047	2.29	**
SPELL_MAX_TEMP²	-0.0005	-2.26	*	-0.00001	-0.01		-0.0008	-1.87	*	-0.0008	-0.98		0.0009	3.59	***
SPELL_MAX_TEMP² × *DURATION*	-0.00004	-3.07	**	-0.00002	-0.55		-0.0001	-2.11	*	0.0001	1.26		-0.0001	-2.46	**
DURATION	-0.0194	-2.99	**	-0.0152	-0.71		-0.034	-3.86	***	0.0507	1.02		-0.0669	-2.2	*
LEVERAGE	-0.2203	-5.47	***	-0.0113	-0.15		-0.1312	-2.17	*	-0.1673	-3.53	***	-0.1564	-2.38	**
CONSTANT	0.807	6.17	***	0.9982	3.98	***	0.628	4.08	***	0.515	1.01		1.7183	8.22	***
R Square Adj.	4.45%			0.10%			10.19%	0		6.20%			4.08%		
Observations	108,111			13,606			31,458	0		33,309			25,860		
Panel B				6.Non-Energy			7.Non-Labor-intensive			8.non-UK.FR.DE			9.High latitude		
SPELL_MAX_TEMP				0.027	2.09	*	0.0204	1.5		0.0074	0.7		-0.0111	-0.74	
SPELL_MAX_TEMP × *DURATION*				0.0019	2.7	**	0.0011	1.4		0.0017	2.72	**	0.0008	0.81	
SPELL_MAX_TEMP²				-0.0006	-2.02	*	-0.0004	-1.62		-0.0002	-0.76		0.0005	1.04	
SPELL_MAX_TEMP² × *DURATION*				-0.00004	-2.65	**	0.00002	-1.71		-0.00004	-3.11	**	-0.00002	-0.67	
DURATION				-0.02	-2.51	**	-0.0110	-1.13		-0.0167	-2.2	*	-0.0107	-1.27	
LEVERAGE				-0.2486	-6.09	***	-0.2540	-6.23	***	-0.2119	-4.48	***	-0.2973	-3.9	***
CONSTANT				0.7954	5.36	***	0.8765	5.49	***	0.9521	7.78	***	1.1651	9.59	***
R Square Adj.				4.91%			1.91%			4.53%			12.08%		
Observations				94,505			76,653			74,802			17,094		
Tests of differences															
SPELL_MAX_TEMP²x DURATION (A-B)				0.00002	1.52		-.00004	-0.02		0.00014	0.70		-0.00007	-1.89	*
Panel C	1.All			10.Weekday			11.Non-Summer			12.Distant			13.Vulnerable		
SPELL_MAX_TEMP	0.0243	2.24	*	0.0247	1.65		0.0055	0.52		0.0306	2.37	**	-0.0006	-0.07	
SPELL_MAX_TEMP × *DURATION*	0.0018	3.17	**	0.0017	2.3	**	0.0019	1.82		0.0018	2.17	*	0.002	3.88	***
SPELL_MAX_TEMP²	-0.0005	-2.26	*	-0.0005	-1.53		0.00003	0.1		-0.0006	-2.32	**	-0.00001	-0.07	
SPELL_MAX_TEMP² × *DURATION*	-0.00004	-3.07	**	-0.00004	-2.65	**	-0.0001	-2.02	*	-0.00004	-2.07	*	-0.00004	-4.42	***
DURATION	-0.0194	-2.99	**	-0.0188	-2.01	*	-0.0133	-1.41		-0.0199	-2.17	*	-0.0211	-3.19	**
LEVERAGE	-0.2203	-5.47	***	-0.2151	-4.68	***	-0.2192	-4.69	***	-0.124	-2.71	**	-0.2137	-4.17	***
CONSTANT	0.807	6.17	***	0.7894	4.79	***	0.9358	8.41	***	0.7412	4.6	***	1.0148	9.74	***
R Square Adj.	4.45%			4.60%			5.10%			5.15%			6.06%		
Observations	108,111			85,235			44,522			66,467			59,283		
Panel D				14.Weekend			15.Summer			16.Close			17.Non-Vulnerable		
SPELL_MAX_TEMP				0.0043	0.18		0.0511	1.85	*	0.0021	0.07		0.0224	1.1	
SPELL_MAX_TEMP × *DURATION*				0.0025	1.04		0.0012	0.83		0.0003	0.24		-0.0021	-1.22	
SPELL_MAX_TEMP²				-0.0001	-0.29		-0.001	-2.06	*	-0.0002	-0.28		-0.0002	-0.43	
SPELL_MAX_TEMP² × *DURATION*				-0.0001	-1.1		0.00002	-0.88		0.00001	-0.37		0.0001	1.23	
DURATION				-0.0282	-1.02		-0.014	-0.74		-0.0026	-0.16		0.0191	1.11	
LEVERAGE				-0.215	-4.87	***	-0.2161	-5.27	***	-0.3251	-6.57	***	-0.1359	-2.92	**
CONSTANT				1.068	4.04	***	0.46	1.33		1.0262	2.83	**	0.7529	3.63	***
R Square Adj.				5.13%			4.23%			4.40%			5.25%		
Observations				22,876			63,589			25,897			48,290		
Tests of differences															
SPELL_MAX_TEMP²x DURATION (C-D)				0.00002	1.89	*	-.00004	-1.15		0.00014	0.17		-0.00007	-0.79	

This table summarizes the coefficients for Eq. (2) stated as $SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP \times DURATION + \beta_3 SPELL\_MAX\_TEMP^2 + \beta_4 SPELL\_MAX\_TEMP^2 \times DURATION + \beta_5 DURATION + \beta_6 LEVERAGE + FE + \varepsilon$ for observations in Low Subs. in the Group partition. Results for observations in High Subs. in the Group partition are available on request. The results are also split by energy, labor intensity, *UK.FR.DE* vs other, latitude, day-of-week, season, closeness to major EU city, and vulnerability to climate change. The regressions control for year and sector fixed effects to adjust for unrelated time trends and sector differences. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

Table 6. Response of the sales-to-assets ratio to extreme high temperature spells: By period

Period	All			2011–2013			2014–2016			2017–2019		
Variable	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A. Distant location, Low subs. in Group												
SPELL_MAX_TEMP	0.0544	5.38	***	0.0745	4.10	*	0.0432	3.22	*	0.0462	3.37	*
SPELL_MAX_TEMP^2	-0.0011	-5.57	***	-0.0015	-4.04	*	-0.0010	-3.24	*	-0.0008	-2.64	
DURATION	0.0005	0.31		-0.0025	-1.06		0.0034	1.06		0.0006	0.19	
LEVERAGE	-0.1238	-2.70	**	-0.1641	-3.77	*	-0.1882	-3.55	*	0.0091	0.20	
CONSTANT	0.4773	3.64	***	0.2975	1.35		0.6388	4.04	*	0.3692	2.74	
R Square Adj.	5.14%			5.30%			5.50%			5.01%		
Observations	66,249			23,855			22,639			19,755		
Panel B. Close location, Low subs. in Group												
SPELL_MAX_TEMP	0.0067	0.47		0.0259	1.30		-0.0225	-17.97	***	0.0545	1.95	
SPELL_MAX_TEMP^2	-0.0003	-1.00		-0.0007	-1.86		0.0003	4.17	*	-0.0012	-2.12	
DURATION	-0.0008	-0.50		-0.0032	-5.54	**	0.0040	1.30		-0.0020	-0.75	
LEVERAGE	-0.3254	-6.58	***	-0.3616	-7.98	**	-0.3849	-7.30	**	-0.2050	-3.16	*
CONSTANT	1.0019	5.86	***	0.8723	3.45	*	1.2737	20.75	***	0.3043	1.02	
R Square Adj.	4.40%			4.74%			4.84%			3.89%		
Observations	25,724			9,413			8,795			7,516		
Tests of differences: Distant less Close location												
Low subs. in group												
SPELL_MAX_TEMP (A-B)	0.0478	5.72	***	0.0487	2.96	*	0.0657	12.51	***	-0.0083	-0.28	
SPELL_MAX_TEMP^2 *(A-B)*	-0.0008	-4.59	***	-0.0008	-2.88		-0.0013	-13.22	***	0.0004	0.65	
Panel C. Distant location, High subs. in Group												
SPELL_MAX_TEMP	0.0210	1.86	*	0.0351	3.02	*	0.0090	0.97		0.0349	1.09	
SPELL_MAX_TEMP^2	-0.0004	-1.83		-0.0007	-3.16	*	-0.0002	-1.16		-0.0005	-0.91	
DURATION	0.0002	0.08		-0.0017	-0.35		0.0042	2.31		-0.0020	-0.64	
LEVERAGE	0.8601	23.2	***	0.7833	24.69	***	0.8938	25.62	***	0.9268	25.97	***
CONSTANT	0.2549	2.05	*	0.1371	0.81		0.3300	3.52	*	0.0023	0.01	
R Square Adj.	9.72%			8.69%			10.35%			10.74%		
Observations	64,987			23,159			22,406			19,422		
Panel D. Close location, High subs. in Group												
SPELL_MAX_TEMP	-0.0286	-3.00	**	-0.0336	-1.82		-0.0397	-3.42	*	-0.0323	-1.58	
SPELL_MAX_TEMP^2	0.0004	2.06	*	0.0004	1.17		0.0008	3.54	*	0.0005	1.10	
DURATION	-0.0002	-0.08		-0.0020	-2.22		0.0063	1.40		-0.0021	-0.81	
LEVERAGE	0.8665	19.47	***	0.7591	15.25	***	0.8971	22.57	***	0.9394	22.26	***
CONSTANT	0.7897	7.23	***	0.9940	5.07	**	0.7078	6.32	**	0.8774	3.70	*
R Square Adj.	10.00%			8.50%			10.56%			11.49%		
Observations	40,121			14,389			13,793			11,939		
Tests of differences: Distant less Close location												
High subs. in group												
SPELL_MAX_TEMP (C-D)	0.0496	3.71	***	0.0687	4.06	*	0.0487	3.63	*	0.0672	4.85	**
SPELL_MAX_TEMP^2 *(C-D)*	-0.0008	-3.06	**	-0.0011	-3.59	*	-0.0010	-3.65	*	-0.0010	-3.70	*

This table summarizes the coefficients for Eq. (1) for three intervals of the study period split on the shortest distance of a firm's location to UK and EU capital cities (Distant versus Close) and the number of subsidiaries in the group. ***=p<0.01, **=p<0.05, *=p<0.10. Within each three-year interval and for the sample as a whole, the regressions control for year and sector fixed effects. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

Table 7. Response of future ESG score to extreme high temperature spells

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	.Sig.
Panel A	1.All			2.Energy			3.Labor-intensive			4.UK.DR.DE			5.Low Latitude		
SPELL_MAX_TEMP	0.3090	2.03	**	0.6288	1.26		0.1664	0.47		1.4533	3.55	***	-0.2185	-0.27	
SPELL_MAX_TEMP²	-0.0086	-2.61	***	-0.0128	-1.26		-0.0062	-0.80		-0.0314	-3.79	***	0.0018	0.13	
DURATION	0.0483	0.05	**	-0.1296	0.25		0.0585	0.33		0.0244	0.47		0.0590	0.28	
LEVERAGE	2.1944	1.08		9.9886	0.78		5.9645	0.98		2.1412	0.51		11.7334	1.19	
CONSTANT	0.2180	0.11		-7.6157	-0.75		-0.2784	-0.05		-13.0993	-2.40	**	-0.2289	-0.02	
R Square Adj.	0.3001			0.3255			0.2535			0.2941			0.4012		
Observations	2,428			162			467			1,197			237		
Panel B				6.Non-Energy			7.Non-Labor-intensive			8.Non-UK.DR.DE			9.High Latitude		
SPELL_MAX_TEMP				0.2966	1.86	*	0.3462	2.07	**	-0.0025	-0.01		0.3313	0.63	
SPELL_MAX_TEMP²				-0.0085	-2.44	**	-0.0092	-2.56	**	-0.0025	-0.68		-0.0085	-0.56	
DURATION				0.0592	0.02	**	0.0466	0.08	*	0.0825	0.02	**	-0.0538	0.37	
LEVERAGE				1.4002	0.62		0.9720	0.41		2.2893	1.13		5.5462	0.73	
CONSTANT				0.8296	0.39		0.4921	0.22		3.1988	1.60		-0.1504	-0.03	
R Square Adj.				0.2959			0.3073			0.3134			0.2684		
Observations	2,428			2,266			1,960			1,231			438		
Panel C	1.All			10.Weekday			11.Non-Summer			12.Low Subs. in Group			13.Vulnerable		
SPELL_MAX_TEMP	0.3090	2.03	**	0.2918	1.94	*	0.0930	0.18		-0.1528	-0.31		-0.0843	-0.39	
SPELL_MAX_TEMP²	-0.0086	-2.61	***	-0.0080	-2.46	**	-0.0016	-0.15		0.0037	0.35		-0.0012	-0.28	
DURATION	0.0483	0.05	**	0.0465	0.06	*	0.0204	0.64		0.0545	0.28		0.0909	0.03	**
LEVERAGE	2.1944	1.08		1.3072	0.60		1.1467	0.38		0.2147	0.06		3.2370	0.52	
CONSTANT	0.2180	0.11		0.8240	0.40		2.4358	0.38		5.2421	0.88		3.6682	0.79	
R Square Adj.	0.3001			0.3291			0.3343			0.3346			0.3398		
Observations	2,428			2.042			605			317			727		
Panel D				14.Weekend			15.Summer			16.High Subs. in Group			17.Non-Vulnerable		
SPELL_MAX_TEMP				0.2846	0.35		0.1368	0.48		0.3534	2.19	**	0.4655	2.21	**
SPELL_MAX_TEMP²				-0.0085	-0.53		-0.0066	-1.11		-0.0099	-2.83	***	-0.0115	-2.49	**
DURATION				-0.1102	0.33		0.0874	0.02	**	0.0451	0.10		0.0308	0.30	
LEVERAGE				4.8658	0.92		2.1500	0.84		1.9496	0.81		2.3191	1.13	
CONSTANT				1.0124	0.09		2.6257	0.72		0.0341	0.02		-1.6101	-0.63	
R Square Adj.				0.3196			0.2496			0.3007			0.2959		
Observations				135			1470			2075			1625		

This table summarizes the coefficients for Eq. (6) stated as $\Delta ESG\_SCORE = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon$ for the full sample and partitions of the full sample. The dependent variable is the change in a firm's ESG score over *four* years from year t-1 to t+3, where year t is the year of measurement of *SPELL_MAX_TEMP* and the other variables. The regressions control for firm fixed effects. Standard errors are clustered by firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

Table 8. Response of future emissions to extreme high temperature spells

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A	1.All			2.Energy			3.Labor-intensive			4.UK.DR.DE			5.Low Latitude		
SPELL_MAX_TEMP	-256.8	-2.13	**	-2942.0	-1.77	*	5.7	0.06		-79.3	-0.24		-415.8	-0.90	
SPELL_MAX_TEMP^2	6.7	2.02	**	76.1	1.85	*	0.9	0.40		5.5	0.69		8.7	0.95	
DURATION	44.9	1.93	*	100.5	0.60		13.3	1.27		85.1	2.30	**	53.6	0.82	
LEVERAGE	79.6	0.05		-11700.0	-1.47		1499.4	1.16		-1851.7	-0.96		3639.9	0.43	
CONSTANT	1327.6	1.10		30200.0	1.83	*	-1751.8	-1.20		-2150.5	-0.62		1927.4	0.21	
R Square Adj.	15.9%			16.1%			23.7%			17.6%			16.6%		
Observations	6,850			276			1,413			3,001			745		
Panel B				6.Non-Energy			7.Non-Labor-intensive			8.Non-UK.DR.DE			9.High Latitude		
SPELL_MAX_TEMP				-146.7	-1.41		-322.0	-2.13	**	-113.2	-1.14		-139.2	-0.98	
SPELL_MAX_TEMP^2				3.8	1.27		8.1	1.94	*	2.2	0.75		4.2	0.96	
DURATION				42.7	1.82	*	54.0	1.80	*	-6.5	-0.31		1.8	0.10	
LEVERAGE				700.1	0.46		-346.9	-0.18		1092.2	0.56		264.1	0.36	
CONSTANT				69.6	0.07		2101.7	1.38		1254.5	0.90		936.2	0.76	
R Square Adj.				16.1%			15.8%			15.1%			25.8%		
Observations				6,573			5,433			3,848			1,349		
Panel C	1.All			10.Weekday			11.Non-Summer			12.Low Subs. in Group			13.Vulnerable		
SPELL_MAX_TEMP	-256.8	-2.13	**	-252.0	-1.71	*	-118.2	-0.44		33.4	0.97		-270.9	-1.84	*
SPELL_MAX_TEMP^2	6.7	2.02	**	6.5	1.60		2.8	0.40		-0.5	-0.69		3.3	0.94	
DURATION	44.9	1.93	*	63.0	1.97	**	-2.0	-0.07		-12.5	-1.56		58.3	1.83	*
LEVERAGE	79.6	0.05		-444.2	-0.30		1206.3	0.68		35.0	0.04		-1920.6	-0.41	
CONSTANT	1327.6	1.10		1273.6	0.94		287.0	0.10		-168.3	-0.20		4902.7	1.54	
R Square Adj.	15.9%			19.2%			32.9%			32.1%			13.5%		
Observations	6,850			5,588			1,958			1,955			2,676		
Panel D				14.Weekend			15.Summer			16.High Subs. in Group			17.Non-Vulnerable		
SPELL_MAX_TEMP				-876.6	-2.09	**	-234.4	-0.67		-378.5	-2.27	**	-327.6	-1.49	
SPELL_MAX_TEMP^2				19.5	2.13	**	5.3	0.69		9.4	2.07	**	10.1	1.64	
DURATION				-32.3	-1.56		42.6	1.45		71.1	2.13	**	30.6	0.99	
LEVERAGE				1584.1	1.43		-1907.9	-0.70		377.6	0.16		510.9	0.44	
CONSTANT				9621.2	2.12	**	2869.9	0.68		1863.5	1.02		1075.9	0.78	
R Square Adj.				35.0%			19.1%			15.8%			20.6%		
Observations				486			3,834			4,707			4,033		

This table summarizes the coefficients for Eq. (6) stated as $\Delta EMISSIONS = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + FE + \varepsilon$ for the full sample and partitions of the full sample. The dependent variable is the change in the sum of a firm's Scope 1, 2, and 3 emissions over four years from year *t*-1 to *t*+3, where year *t* is the year of measurement of *SPELL_MAX_TEMP* and the other variables. The regressions control for firm fixed effects. Standard errors are clustered by firm. ***=p<0.01, **=p<0.05, *=p<0.10. Appendix B defines the variables.

The Effects of Extreme High Temperature Spells on Financial Performance: Supplementary Analysis

Suppl. Fig. A. Placebo tests of the sales-to-extreme temperature response function

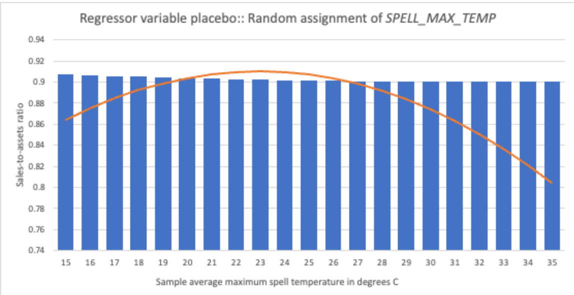


Fig. A.1. After randomizing the row order of *SPELL_MAX_TEMP*

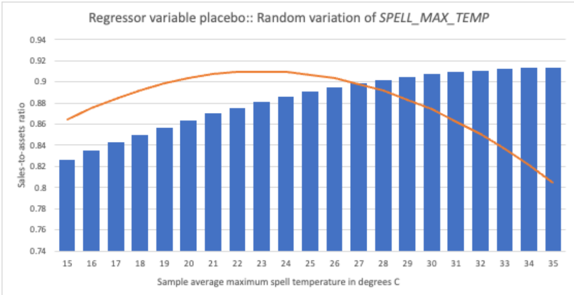


Fig. A.2. After adding random variation to *SPELL_MAX_TEMP*

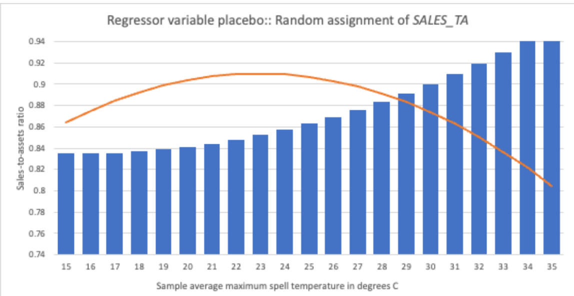


Fig. A.3. After randomizing the row order of *SALES_TA*

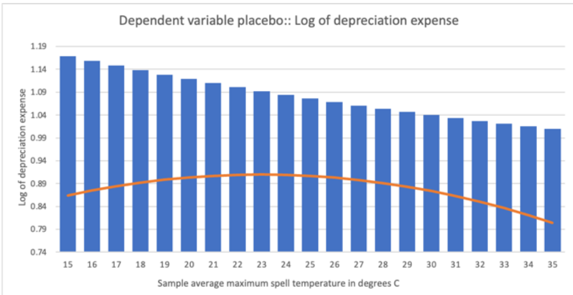


Fig. A4. After replacing *SALES_TA* with the log of depreciation expense

These graphs plot the sample-wide dependent variable based on the regression coefficients for Eq. (1) modified using placebo variables. For comparison, the original findings as per Fig. 2.1 are shown as the hump shaped orange line. For each of Figs. A1–A4, the coefficients for *SPELL_MAX_TEMP* and $SPELL\_MAX\_TEMP^2$ based on Eq. (1) modified using placebo variables are insignificantly different from zero ($p<0.05$). Fig. A1 shows that the sales-to-extreme temperature response function is flat when we assume that *SPELL_MAX_TEMP* is generated by randomizing the row order of the original *SPELL_MAX_TEMP* observations. Fig. A2 shows that the sales-to-extreme temperature response function is positive (but insignificant) when we assume that *SPELL_MAX_TEMP* is generated by adding random variation to the original *SPELL_MAX_TEMP* observations. Fig. A3 shows that the sales-to-extreme temperature response function is positive (but insignificant) when we assume that *SALES_TA* is generated by randomizing the row order of the original *SALES_TA* observations. Fig. A4 shows that the depreciation expense to extreme temperature response function is negative (but insignificant) when we replace *SALES_TA* with the natural log of depreciation expense.

Suppl. Table A1. Controlling for country-level sales

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A	1.All			2.Energy			3.Labor-Intensive			4.UK.FR.DE			5.Low Latitude		
SPELL_MAX_TEMP	0.0438	4.80	***	0.0118	0.87		0.0576	5.23	***	0.0350	2.34	**	0.0026	0.22	
SPELL_MAX_TEMP^2	-0.0010	-5.38	***	-0.0002	-0.81		-0.0012	-5.33	***	-0.0009	-3.22	***	-0.0001	-0.31	
SUM_SPELL_LENGTH	0.0014	1.02		-0.0002	-0.10		0.0021	1.72		0.0030	1.96	*	0.0004	0.26	
LEVERAGE	0.4016	17.97	***	0.3718	6.89	***	0.5362	16.59	***	0.4615	12.94	***	0.3013	7.67	***
WHOLESALE_RETAIL	0.1282	10.62	***	0.0490	2.64	**	0.1420	10.21	***	0.1207	7.87	***	0.0711	5.32	***
CONSTANT	0.0686	0.64		0.4406	2.64	**	-0.3029	-2.27	**	0.2880	1.49		0.4963	3.04	***
Year and Sector FE	Yes			Yes			Yes			Yes			Yes		
R Square Adj.	7.88%			1.79%			11.70%			12.38%			6.81%		
Observations	254,003			25,459			74,732			51,005			63,999		
Panel B				6.Non-Energy			7.Non-Labor-Intens.			8.Non-UK.FR.DE			9.High Latitude		
SPELL_MAX_TEMP				0.0475	4.92	***	0.0367	3.90	***	0.0310	3.67	***	-0.0067	-0.64	
SPELL_MAX_TEMP^2				-0.0011	-5.48	***	-0.0009	-4.65	***	-0.0007	-4.38	***	0.0003	1.11	
SUM_SPELL_LENGTH				0.0017	1.17		0.0012	0.65		0.0012	0.99		0.0022	2.04	*
LEVERAGE				0.4064	18.32	***	0.3466	14.14	***	0.3822	14.47	***	0.4277	8.97	***
WHOLESALE_RETAIL				0.1349	10.64	***	0.1226	10.01	***	0.1334	10.18	***	0.1275	8.54	***
CONSTANT				0.0245	0.22		0.2393	2.20	**	0.2112	2.06	*	0.4538	4.73	***
Year and Sector FE				Yes			Yes			Yes			Yes		
R Square Adj.				8.49%			6.03%			7.44%			12.08%		
Observations				228,544			179,271			202,998			43,240		
Tests of differences															
SPELL_MAX_TEMP (A-B)				-0.0357	-4.05	***	0.0209	1.33		0.0041	-1.330		0.0093	0.86	
SPELL_MAX_TEMP^2 *(A-B)*				0.0009	4.67	***	-0.0003	-0.68		-0.0002	1.160		-0.0004	-1.42	
Panel C	1.All			10.Weekday			11.Non-Summer			12.Low Subs.in Group			13.Vulnerable		
SPELL_MAX_TEMP	0.0438	4.80	***	0.0437	5.74	***	0.0294	3.84	***	0.0562	4.42	***	0.0269	3.46	***
SPELL_MAX_TEMP^2	-0.0010	-5.38	***	-0.0010	-6.01	***	-0.0007	-4.85	***	-0.0012	-4.59	***	-0.0007	-4.43	***
SUM_SPELL_LENGTH	0.0014	1.02		0.0013	0.88		0.0014	0.51		0.0010	0.66		0.0015	1.01	
LEVERAGE	0.4016	17.97	***	0.4057	16.53	***	0.3945	13.70	***	-0.1914	-4.73	***	0.3541	11.74	***
WHOLESALE_RETAIL	0.1282	10.62	***	0.1326	11.56	***	0.1204	9.81	***	0.0549	2.68	**	0.1064	9.92	***
CONSTANT	0.0686	0.64		0.0670	0.74		0.2668	2.93	***	0.3893	2.28	**	0.2995	3.26	***
Year and Sector FE	Yes			Yes			Yes			Yes			Yes		
R Square Adj.	7.88%			8.07%			8.23%			5.70%			7.81%		
Observations	254,003			202,214			109,881			89,438			159,188		
Panel D				14.Weekend			15.Summer			16.High Subs. in Group			17.Non-Vulner.		
SPELL_MAX_TEMP				0.0367	2.04	*	0.0631	5.55	***	0.0340	3.53	***	0.0464	5.85	***
SPELL_MAX_TEMP^2				-0.0008	-2.24	**	-0.0013	-5.59	***	-0.0008	-3.99	***	-0.0009	-5.99	***
SUM_SPELL_LENGTH				0.0016	1.16		0.0021	1.05		0.0006	0.33		0.0021	1.95	*
LEVERAGE				0.3921	12.79	***	0.4084	14.12	***	1.0323	23.81	***	0.5026	19.67	***
WHOLESALE_RETAIL				0.1145	5.99	***	0.1355	9.08	***	0.4822	14.16	***	0.1699	9.07	***
CONSTANT				0.1530	0.68		-0.2097	-1.40		-0.3162	-3.33	***	-0.1030	-0.89	
Year and Sector FE				Yes			Yes			Yes			Yes		
R Square Adj.				8.17%			7.84%			22.58%			10.86%		
Observations				51,789			144,122			87,396			94,051		
Tests of differences															
SPELL_MAX_TEMP (C-D)				0.0071	3.70	**	-0.0337	-1.71		0.0222	0.89		-0.0195	-2.39	*
SPELL_MAX_TEMP^2 *(C-D)*				-0.0002	-3.77	**	0.0006	0.74		-0.0004	-0.60		0.0002	1.56	

This table summarizes the coefficients for Eq. (1) stated as $SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 SPELL\_MAX\_TEMP^2 + \beta_3 DURATION + \beta_4 LEVERAGE + \beta_5 WHOLESALE\_RETAIL + FE + \varepsilon$ for the full sample and partitions of the full sample. The regressions control for year and sector fixed effects to adjust for unrelated time trends and sector differences. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. *WHOLESALE_RETAIL* = retail and wholesale sales in country of location in year *t* scaled by the average total assets at the beginning of year *t* of firms in each country of location. Appendix B of the main text defines the other variables.

Suppl. Table A2. Controlling for group size and interacting group size with extreme temperature

	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.	Coeff.	*t*-stat	Sig.
Panel A	1.All			2.Energy			3.Labor-Intensive			4.UK.FR.DE			5.Low latitude		
SPELL_MAX_TEMP	0.0692	5.06	***	0.0195	1.12		0.0961	4.66	***	0.0343	1.86	*	-0.0163	-1.43	
GROUP_SIZE	0.5703	4.06	***	0.5437	2.10	*	0.7170	3.75	***	-0.2462	-1.43		-0.1269	-0.46	
GROUP_SIZE×SPELL_MAX_TEMP	-0.0422	-3.55	***	-0.0423	-1.99	*	-0.0548	-3.28	**	0.0125	0.93		0.0100	0.47	
SPELL_MAX_TEMP^2	-0.0015	-5.22	***	-0.0004	-1.24		-0.0019	-4.34	***	-0.0008	-1.85	*	0.0002	1.14	
GROUP_SIZE×SPELL_MAX_TEMP^2	0.0009	3.48	***	0.0009	2.03	*	0.0010	2.78	**	-0.0003	-0.95		-0.0001	-0.16	
DURATION	0.0011	0.61		-0.0001	-0.04		0.0016	1.05		-0.0005	-0.35		-0.0002	-0.14	
LEVERAGE	0.4526	15.37	***	0.3955	5.54	***	0.6118	13.67	***	0.5185	10.98	***	0.3843	7.21	***
WHOLESALE_RETAIL	0.1882	6.97	***	0.0381	1.72		0.1793	6.78	***	0.3704	9.34	***	0.0715	3.25	**
CONSTANT	-0.2850	-1.71		0.4015	1.97	*	-0.8053	-3.37	***	0.1754	0.70		0.7435	5.16	***
R Square Adj.	8.40%			1.66%			12.55%			17.74%			6.97%		
Observations	176834			18985			51409			31484			44735		
Panel B				6.Non-Energy			7.Non-Labor-Intensive			8.Non-UK.FR.DE			9.HIgh-Latitude		
SPELL_MAX_TEMP				0.0762	4.83	***	0.0528	4.31	***	0.0375	3.51	***	-0.0239	-1.71	
GROUP_SIZE				0.6021	3.74	***	0.4757	3.27	**	0.3498	2.99	**	0.0049	0.05	
GROUP_SIZE×SPELL_MAX_TEMP				-0.0448	-3.24	**	-0.0325	-2.72	**	-0.0193	-1.94	*	0.0210	3.00	**
SPELL_MAX_TEMP^2				-0.0017	-4.94	***	-0.0012	-4.74	***	-0.0009	-3.94	***	0.0009	2.16	*
GROUP_SIZE×SPELL_MAX_TEMP^2				0.0009	3.16	**	0.0007	2.85	**	0.0004	2.02	*	-0.0006	-3.86	***
DURATION				0.0013	0.67		0.0009	0.40		0.0011	0.72		-0.0004	-0.25	
LEVERAGE				0.4605	16.06	***	0.3838	12.63	***	0.4611	13.91	***	0.5366	8.44	***
WHOLESALE_RETAIL				0.2073	7.14	***	0.1914	6.75	***	0.1733	6.67	***	0.2320	6.59	***
CONSTANT				-0.3784	-1.98	*	-0.0110	-0.07		0.0499	0.38		0.3968	3.36	***
R Square Adj.				9.23%			6.68%			8.15%			17.04%		
Observations				157849			125425			145350			29015		
Tests of differences															
SPELL_MAX_TEMP (A-B)				-0.0567	-3.71	**	0.0433	0.35		-0.0032	-1.65		0.0076	0.28	
SPELL_MAX_TEMP^2 *(A-B)*				0.0026	6.97	***	0.0022	7.52	***	0.0006	2.99		-0.0010	-2.32	
Panel C	1. All			10.Weekday			11.Non-Summer			12.Low Subs. in Group			13.Vulnerable		
SPELL_MAX_TEMP	0.0692	5.06	***	0.0687	5.79	***	0.0436	4.15	***	0.0562	4.42	***	0.0323	3.41	***
GROUP_SIZE	0.5703	4.06	***	0.5714	3.88	***	0.4623	3.66	***	0.0000	0.00	***	0.4686	3.97	***
GROUP_SIZE×SPELL_MAX_TEMP	-0.0422	-3.55	***	-0.0421	-3.38	***	-0.0330	-2.78	**	0.0000	0.00	***	-0.0228	-2.35	**
SPELL_MAX_TEMP^2	-0.0015	-5.22	***	-0.0015	-5.41	***	-0.0010	-3.95	***	-0.0012	-4.59	***	-0.0008	-4.02	***
GROUP_SIZE×SPELL_MAX_TEMP^2	0.0009	3.48	***	0.0009	3.24	**	0.0007	2.60	**	0.0000	0.00	***	0.0004	2.15	*
DURATION	0.0011	0.61		0.0009	0.47		0.0008	0.24		0.0010	0.66		0.0015	0.92	
LEVERAGE	0.4526	15.37	***	0.4592	14.60	***	0.4408	12.67	***	-0.1914	-4.73	***	0.4254	11.21	***
WHOLESALE_RETAIL	0.1882	6.97	***	0.1929	7.39	***	0.1712	7.38	***	0.0549	2.68	**	0.1387	6.49	***
CONSTANT	-0.2850	-1.71		-0.2808	-1.97	*	0.0454	0.34		0.3893	2.28	**	0.1153	1.02	
R Square Adj.	8.40%			8.71%			8.45%			5.70%			8.51%		
Observations	176834			141958			76563			89438			113948		
Panel D				14.Weekend			15.Summer			16.High Subs. in Group			17.Non-Vulner.		
SPELL_MAX_TEMP				0.0574	1.88	*	0.1004	5.24	***	0.0340	3.53	***	0.0413	2.44	**
GROUP_SIZE				0.4327	1.66		0.7561	4.37	***	0.0000	0.00	***	0.2715	1.58	
GROUP_SIZE×SPELL_MAX_TEMP				-0.0314	-1.42		-0.0578	-4.08	***	0.0000	0.00		-0.0137	-0.84	
SPELL_MAX_TEMP^2				-0.0013	-2.07	*	-0.0021	-5.11	***	-0.0008	-3.99	***	-0.0005	-1.19	
GROUP_SIZE×SPELL_MAX_TEMP^2				0.0007	1.66		0.0012	4.05	***	0.0000	0.00		0.0000	0.09	
DURATION				0.0012	0.72		0.0017	0.69		0.0006	0.33		-0.0003	-0.21	
LEVERAGE				0.4378	10.39	***	0.4640	12.81	***	1.0323	23.81	***	0.5630	15.49	***
WHOLESALE_RETAIL				0.1750	4.45	***	0.2052	6.50	***	0.4822	14.16	***	0.3391	8.63	***
CONSTANT				-0.1456	-0.37		-0.7079	-3.05	**	-0.3162	-3.33	***	-0.2531	-1.28	
R Square Adj.				8.59%			8.66%			22.58%			15.37%		
Observations				34876			100271			87396			62234		
Tests of differences															
SPELL_MAX_TEMP (C-D)				0.0113	3.91	**	-0.0568	-1.09		0.0222	0.89		-0.0091	0.97	
SPELL_MAX_TEMP^2 *(C-D)*				0.0021	5.31	***	0.0028	7.71	***	0.0008	3.99	**	0.0009	3.34	**

Continued on next page.

Suppl. Table A2, contd.

This table summarizes the coefficients for Eq. (1) stated as $SALES\_TA = \alpha + \beta_1 SPELL\_MAX\_TEMP + \beta_2 GROUP\_SIZE + \beta_3 GROUP\_SIZE \times SPELL\_MAX\_TEMP + \beta_4 SPELL\_MAX\_TEMP^2 + \beta_5 GROUP\_SIZE \times SPELL\_MAX\_TEMP^2 + \beta_6 DURATION + \beta_7 LEVERAGE + \beta_8 WHOLESALE\_RETAIL + FE + \varepsilon$ for the full sample and partitions of the full sample. The regressions control for year and sector fixed effects to adjust for unrelated time trends and sector differences. Standard errors are clustered by year and firm. ***=p<0.01, **=p<0.05, *=p<0.10. *WHOLESALE_RETAIL* = retail and wholesale sales in country of location in year *t* scaled by the average total assets at the beginning of year *t* of firms in each country of location. Appendix B of the main paper defines the other variables.

Suppl. Table A3. Impact threshold of a confounding variable (ITCV) analysis

	1.All		2.Energy		3.Labor-intensive		4.UK.FR.DE		5.Low Latitude	
	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B
SPELL_MAX_TEMP	56.30%	1.00%	96.15%	1.04%	69.78%	1.45%	*19.35%*	0.17%	22.18%	-0.20%
SPELL_MAX_TEMP^{2}	57.49%	0.52%	79.57%	3.01%	70.61%	0.00%	33.91%	3.78%	28.76%	0.31%
DURATION	96.04%	0.05%	94.38%	0.80%	32.63%	-0.57%	98.51%	**0.42%**	29.29%	0.00%
LEVERAGE	87.06%	0.00%	82.18%	0.00%	89.19%	-1.06%	90.32%	0.04%	85.29%	**-2.35%**
			6.Non-Energy		7.Non-Labor-intensive		8.non-UK.FR.DE		9.High latitude	
			Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B
SPELL_MAX_TEMP			57.67%	0.45%	42.12%	0.27%	36.20%	0.23%	90.41%	0.74%
SPELL_MAX_TEMP^{2}			58.91%	0.39%	43.30%	0.52%	46.13%	0.04%	12.46%	2.46%
DURATION			94.70%	0.00%	89.94%	0.10%	55.41%	-0.07%	12.76%	0.00%
LEVERAGE			86.60%	0.00%	83.69%	-0.01%	81.15%	**-0.92%**	81.17%	**-0.82%**
	1. All		10.Weekday		11.Non-Summer		12.Low Subs. in Group		13.Vulnerable	
	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B
SPELL_MAX_TEMP	56.30%	1.00%	58.44%	0.50%	48.60%	0.48%	57.05%	0.74%	39.39%	0.29%
SPELL_MAX_TEMP^{2}	57.49%	0.52%	57.24%	1.04%	52.24%	0.09%	57.73%	0.55%	45.41%	0.09%
DURATION	96.04%	0.05%	91.11%	0.09%	72.83%	-0.47%	94.06%	0.14%	31.01%	-0.07%
LEVERAGE	87.06%	0.00%	85.28%	0.01%	86.15%	-0.25%	64.25%	0.01%	73.17%	**-1.19%**
			14.Weekend		15.Summer		16.High Subs.in Group		17.Non-Vulner.	
			Col. A	Col. B	Col. A	Col. B	Col. A	Col. B	Col. A	Col. B
SPELL_MAX_TEMP			17.83%	-0.12%	59.04%	0.59%	9.61%	-2.20%	19.22%	-0.08%
SPELL_MAX_TEMP^{2}			4.24%	0.00%	57.14%	1.38%	12.87%	2.46%	82.24%	3.93%
DURATION			24.96%	-0.07%	84.01%	0.02%	89.87%	0.50%	93.55%	0.04%
LEVERAGE			85.57%	**-0.89%**	83.04%	0.15%	92.99%	-0.02%	92.03%	0.03%

This table summarizes (i) the percentage of cases needed to be measured with bias so that the effect of *SPELL_MAX_TEMP* on *SALES_TA* would be zero and (ii) the minimum threshold partial correlation as a function of the correlation relation between *SPELL_MAX_TEMP* and *SALES_TA* such that an omitted variable could invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is non-zero. Col. A percentages: These are the percentages of cases that would have to be replaced to generate an effect of zero. On balance, these percentages will be higher to invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is zero. Col. B percentages: The first is the threshold correlation that an omitted covariate would have with the dependent variable (*SALES_TA*) to invalidate the inference that the coefficient for *SPELL_MAX_TEMP* is non-zero. This second set of percentages are the threshold correlations associated with the other covariates in the regression model. If either of the correlations for *DURATION* or *LEVERAGE* exceeds the threshold for *SPELL_MAX_TEMP*, this increases the chances that a covariate other than predictor of interest (i.e., *SPELL_MAX_TEMP*) could explain the findings. These percentages are shown in bold in the table.