Journal of Financial Economics 150 (2023) 1–45

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Temperature shocks and industry earnings news☆

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ARTICLE INFO

Article history:
Received 5 December 2022
Revised 17 July 2023
Accepted 18 July 2023
Available online 4 August 2023

JEL classification:
G12
G14
Q54

Keywords:
Climate shocks
Temperature extremes
Earnings predictability
Sell-side analysts
Stock returns

ABSTRACT

Climate scientists project rising average temperatures and increasing frequency of temperature extremes. We study how extreme temperatures affect corporate profitability across different industries and whether sell-side analysts understand these relationships. We combine granular daily data on temperatures across the continental U.S. with locations of public companies' establishments and build a panel of quarterly firm-level temperature exposures. Extreme temperatures significantly impact earnings in over 40% of industries, with bi-directional effects that harm some industries while others benefit. Analysts and investors do not immediately react to observable intra-quarter temperature shocks, though earnings forecasts account for temperature effects by quarter-end in many industries.

1. Introduction

Climate scientists project an increase in both the mean and volatility of global temperatures, suggesting that exposure to more severe extreme weather events is a virtual certainty. In particular, the Intergovernmental Panel on Climate Change (IPCC) forecasts that extreme weather events will become more frequent, have longer duration, and exhibit stronger intensity over time (IPCC, 2014). In the United States, climate scientists project that the frequency of heat waves has already more than doubled and that some locations will experience fourfold increases by mid-century (Lau and Nath, 2012). Accordingly, the topic of climate change has attracted the attention of economists interested in assessing its potential effects. For example, extreme temperatures have been shown to affect agricultural productivity, labor supply, and aggregate industrial output (Fisher et al., 2012; Graff-Zivin and Neidell, 2014; Jones and Olken, 2010; Hsiang, 2010).

More recently, Addoum et al. (2020) examine the impact of exposure to extreme temperatures at economic es-

☆ David Hirshleifer and Nikolai Roussanov were the editors for this article. We thank an anonymous referee, Rui Albuquerque, Darwin Choi, Caroline Flammer, Todd Gerarden, Xavier Giroud, David Hirshleifer, Harrison Hong, Byoung-Hyoun Hwang, Andrew Karolyi, Frank Weikai Li, Charles Martineau, Randall Morck, Justin Murfin, Nora Pankratz, José Scheinkman, Wolfram Schlenker, Mike Simutin, Laura Starks, Margarita Tsoutsoura, Harry Turtle, Zigan Wang, Scott Yonker, and conference and seminar participants at the AFA Annual Meeting, Alberta Frontiers in Finance Conference, Cornell Climate and Finance Workshop, EFA Annual Meeting, FMA Annual Meeting, Geneva Summit on Sustainable Finance, NFA Annual Conference, ICPM Discussion Forum, RFS-Columbia Climate Finance Workshop, Shenzhen Sustainable Finance Forum, Wharton Climate and Commodities Conference, Colorado State University, Concordia University, Cornell University, Florida International University, Singapore Management University, University of Cambridge, University of Georgia, and University of South Florida for helpful comments. We thank SafeGraph for providing establishment visit data. We also thank Alok Kumar and Danling Jiang for sharing analyst data. Finally, we acknowledge financial support through a Research Award from the International Centre for Pension Management at the University of Toronto, as well as best paper awards from the Geneva Summit on Sustainable Finance and the NFA Annual Conference. We are responsible for any errors and omissions.

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https://doi.org/10.1016/j.jfineco.2023.07.002

tablishments in the United States. Using a large sample yielding precise estimates, they find no evidence that temperature exposures significantly affect establishment-level sales or productivity. These findings are consistent with those of Dell et al. (2012), who show that the negative effects of temperature on aggregate economic growth are concentrated among developing countries and are tenuous in richer economies. While Addoum et al. (2020) find no population-level effects associated with extreme temperatures, certain sectors of the economy may still exhibit sensitivity to extreme temperatures and such sensitivities may be pronounced only during certain months or seasons. Furthermore, the effects associated with extreme temperatures may be bi-directional. For example, relatively cold winter weather may benefit ski resorts and nearby hotels and restaurants. In contrast, hotels and restaurants may be hurt by cold extremes in the summer months, but experience an uptick in sales and profitability amid hot weather. As a result, estimation of population average effects may mask interesting and economically important variation.

Motivated by these observations, the aim of this paper is to characterize how extreme temperature events affect industry-level earnings and stock prices in the United States. Specifically, we estimate the industry-level profitability effects of time-variation in quarterly temperature exposures at firms' establishment locations using a flexible specification widely used in the climate literature. We also examine whether key market participants, sell-side analysts and investors, understand the relationship between extreme temperatures and corporate profitability.

To perform our analysis, we build a detailed panel of U.S. firms' temperature exposures (i.e., time spent at different temperatures). We use data from several sources. First, we obtain granular climate data from the PRISM Climate Group, the U.S. Department of Agriculture's official climatological database.[1] The PRISM data detail daily temperatures across 481,631 16-square-kilometer (i.e., 4×4km) grids covering the continental United States from 1981 to 2015. We then combine the PRISM climate data with information on U.S. public firms' geographic footprints to generate measures of weather exposure over the course of firms' fiscal quarters. Specifically, we obtain establishment-level data from the NETS database, which provides addresses for each U.S. establishment owned by a publicly traded company over the period from 1990 to 2015.

We ask several questions regarding the role of extreme temperature events in financial markets. First, we ask how extreme temperature exposure affects firm profitability in the United States. Specifically, is the level of exposure to extreme temperatures a useful predictor of quarterly firm earnings? If so, are the predictive effects of extreme temperatures confined to agriculture-related firms, or do they extend across a wider set of industries? Following the climate literature (e.g. Schlenker and Roberts, 2009), we adopt a flexible estimation methodology that allows the detection of nonlinearities and critical thresholds in the effect of temperature on profitability.[2]

We examine the effect of temperature extremes on the profitability of companies in 59 different industries and find that earnings exhibit sensitivity to extreme temperatures in over 40% (24 out of 59) of the industries. The effects of temperature extremes apply to a wide range of industries. The sectors that are the most affected include consumer discretionary (leisure products; textiles, apparel and luxury goods; hotels and restaurants; beverages; and specialty retail), industrials (aerospace and defense; airlines; construction and engineering; and machinery), utilities (electric utilities; gas utilities; and multi-utilities) and health care (health care equipment; pharmaceuticals; and life science tools), among others.[3]

We show that hot and cold temperature extremes affect this diverse set of industries in varying ways during different seasons. In particular, extremely hot summers and extremely cold spring temperatures tend to be damaging for earnings, while a warm autumn generally has a positive effect. Heat waves in the summer (Q3) are consistently bad for corporate earnings: four industries (construction and engineering; leisure products; gas utilities; and capital markets) report significantly lower corporate earnings. Extremely cold temperatures in spring (Q2) are also generally bad news for corporate earnings. Five industries, several of which are travel related (airlines; hotels and restaurants; beverages; textile, apparel, and luxury goods; and pharmaceuticals), have lower earnings, while two other industries (life science tools; and leisure products) have significantly higher earnings.

Meanwhile, warm autumn (Q4) extremes are generally good for corporate earnings: three industries (airlines; metals and mining; and capital markets) report significantly higher earnings, although one industry (machinery) reports lower earnings. Interestingly, the same industry can be affected by both extreme hot and cold temperatures. For instance, earnings for electric utilities are hurt by both extremely warm winters and cool summers.

[1] The PRISM weather data offer several advantages over other temperature data sources. For example, NASA GISSTEMP data are only available at the monthly frequency. NOAA data are restricted to only certain weather stations offering limited coverage, and are subject to potentially important errors (Fisher et al., 2012). The PRISM data are publicly available at: http://www.prism.oregonstate.edu.

[2] We do not explicitly define temperature extremes, since the cutoffs at which very high or low temperatures affect corporate earnings are likely to differ across industries. For example, the climate impact literature finds that crop yields are typically affected by temperatures above 29–32°C (e.g. Schlenker and Roberts, 2009; Fisher et al., 2012; Gammans et al., 2017) and that, in industries with high exposure to climate, labor productivity drops sharply at temperatures above 29°C (Graff-Zivin and Neidell, 2014). Instead, our approach is to estimate the non-linear relationship between observed temperatures and industry-level corporate profitability.

[3] There are two important caveats to the temperature effects that we identify. First, a limitation of our temperature exposure measure is that it captures only temperature shocks experienced at firms' U.S.-based operations. Since many firms have foreign revenue and cost centers, our measure may only partially capture the effects of temperature on earnings. We address this issue by controlling for firms' foreign earnings exposures using data on their geographic financial segments. Second, the temperature effects we document are likely to be net of firms' hedging activities. While these net magnitudes are interesting in their own right, we also isolate the gross effect of extreme temperatures on corporate profitability net of firms' hedging potential. Specifically, we exploit the natural experiment setting of Purnanandam and Weagley (2016), in which the CME Group introduced city-specific weather derivative contracts in a staggered fashion. See Appendix A for further details on these tests.

The extreme temperature-earnings relations we document are also economically significant. In particular, we find that the overall impact of a doubling of the frequency of 5% extreme temperatures implies a 37.4 basis point average change in earnings, amounting to more than half of quarterly earnings for the average firm in our sample. Furthermore, we find that this effect is concentrated among industries for which extreme temperatures are associated with a positive impact on earnings, amounting to an average profitability increase of 48 basis points. Among the complementary set of industries with negative earnings responses, we find that a doubling of the 5% extreme temperature frequency implies a 28 basis point decrease in earnings, on average.

We conduct several sets of tests aimed at understanding the channels that drive the earnings-temperature relations we document. Overall, we find little support for the hypothesis that the crop yield channel is a significant driver of temperature effects among public companies. However, we do find some support for the labor productivity channel advanced by Graff-Zivin and Neidell (2014). In particular, we find that many of the industries with earnings that are sensitive to extreme temperatures also match up with those proposed as having high climate exposure due to heat-induced labor productivity losses. Furthermore, we find that the economic impacts of extreme temperatures are larger in magnitude among industries that Graff-Zivin and Neidell (2014) classify as heat-sensitive.

Over and above the crop yield and labor productivity mechanisms, our results most strongly support a consumer demand channel. Specifically, we find that most of the temperature-sensitive industries we identify are in consumer sectors. Furthermore, the profitability effects among these industries tend to be driven by revenues rather than through operating costs. Our evidence is consistent with the link between extreme weather events and consumer demand proposed by Starr-McCluer (2000). She models the effect of weather on the productivity of time spent in non-market activities such as shopping and recreation. For example, abnormally cold temperatures can hinder travel and keep people away from stores and restaurants, while extreme heat may drive consumers toward indoor activities. As a result, extreme weather can affect industry sales through weather-induced consumer demand shifts across sectors.

We directly test the importance of the consumer demand channel in several ways. First, we utilize SafeGraph data on daily visits to over 870,000 establishments in the hotels & restaurants industry between 2018 and 2021. We find a robust negative effect of spring cold extremes on daily visits. In the full sample, daily visits drop by over 5% on days when temperatures fall below the critical temperature threshold identified in our main tests. Second, we examine the extent to which earnings-temperature relations differs across tradable vs. non-tradable sectors of the economy. Consistent with non-tradable sectors relying heavily on local demand, we find that non-tradable industries exhibit greater economic sensitivity to extreme temperatures than their tradable counterparts. Finally, we examine the importance of weekday vs. weekend extreme temperatures. Among SafeGraph establishments, we document that the negative effect of extreme cold on daily hotel & restaurant visits is amplified on weekends. In contrast, estimating our baseline temperature-earnings relations using only weekday weather reveals that sensitivities are more pronounced among industries where labor productivity is likely to be the dominant channel.

We also investigate the role of extreme temperatures on earnings expectations. In particular, do sell-side analysts understand the relationship between extreme temperature exposure and corporate profitability? In this line of analysis, we aim to test how efficiently analysts, as key drivers of market expectations, aggregate the information content of observable extreme weather events. This line of tests is motivated by several recent studies in finance drawing somewhat opposite conclusions. Hong et al. (2019) use an international drought severity index to demonstrate that food stock investors fail to efficiently discount the risks of droughts, generating predictable patterns in returns. In contrast, Bansal et al. (2016a,b) incorporate temperature-induced disasters into a long-run risks model, and find that these risks are incorporated in the stock returns of value and size portfolios in the U.S. and international markets.

We find that for most industries, analysts anticipate at least part of the earnings shocks associated with temperature extremes by the time earnings are announced. However, the consensus forecasts miss or do not fully account for the effects of temperature extremes in seven industries (leisure products; personal products; life science tools; construction and engineering; trading companies and distributors; commercial services and supplies; and machinery), resulting in predictable earnings surprises. Importantly, there are no industries where analysts adjust their forecasts in the opposite direction to the actual effects associated with temperature shocks.

In our final set of tests, we study how analysts and investors respond to intra-quarter extreme temperature realizations. We define extreme temperature events as days where firms in temperature sensitive industries spend time above or below the critical thresholds identified in our main results. For both analyst forecasts and stock prices, we find that analysts and investors are generally unresponsive to extreme temperature events. Moreover, we find that this slow response is independent of analysts' and investors' political affiliations, local views on climate change, and past experiences with temperature shocks. In light of our earlier finding that analysts anticipate earnings shocks in many industries by quarter-end, these results suggest that analysts learn about the effects of temperature shocks on profitability through indirect channels such as managerial guidance (e.g. Lev and Penman, 1990; Skinner, 1994; Kasznik and Lev, 1995).

Our paper makes several contributions to the literature. First, our study contributes to the new climate finance literature that examines the effects of climate change on various financial market outcomes (Bansal et al., 2016a; 2016b; Hong et al., 2019). The closest papers to ours are those of Addoum et al. (2020) and Pankratz et al. (2023), both of which examine the population-wide effects of extreme temperature exposure on firm performance outcomes. Addoum et al. (2020) demonstrate that sales and productivity growth exhibit negligible temperature effects among the populations of establishments and firms in the United States. In contrast, Pankratz et al. (2023) find that extreme heat has a negative effect on average firm performance among a set of 4,400 single-establishment firms located outside of the United States. We contribute to this literature by documenting significant heterogeneity in extreme temperature effects across industries and seasons. Furthermore, we show that extreme temperature effects are bi-directional, providing an explanation for earlier findings of a tenuous average relation between temperatures and performance outcomes at the firm and aggregate levels in the United States (Dell et al., 2012; Addoum et al., 2020). More broadly, our findings provide support for recent papers documenting the significant impact of extreme temperatures on economic outcomes in the United States, including income (Deryugina and Hsiang, 2017), consumption and investment (Natoli, 2022), and economic growth (Hsiang et al., 2017; Colacito et al., 2019).

Our study is also related to a strand of literature in behavioral finance that links weather to market participants' mood and beliefs. For example, Saunders (1993) finds that the degree of cloud cover in New York City affects daily index returns. Hirshleifer and Shumway (2003) extend this finding to an international setting, demonstrating that sunny weather in the cities of 26 countries' leading stock exchanges is associated with higher index returns. Kamstra et al. (2003) document that investors are more risk averse during winter months with fewer daylight hours. Bassi et al. (2013) confirm this finding in an experimental setting, showing that sunshine and good weather promote risk taking. Goetzmann et al. (2014) demonstrate that cloudy days impact institutional investors' assessment of mispricing and influence their trading decisions. DeHaan et al. (2017) extend these findings to the setting of analysts, showing that analysts experiencing relatively unpleasant weather are slower to respond to the news content in earnings announcements.

Our study differs from these papers in two fundamental ways. First, instead of focusing on sunshine and cloud cover, we focus on the effects of temperature exposure. Importantly, studying the effects of extreme temperatures allows us to assess the potential impact of climate change on companies' earnings as the distribution of temperature exposures changes over time.[4] In contrast, the scientific literature makes no reliable predictions on how variables such as cloud cover and sunshine will evolve as a result of climate change. Second, existing papers linking weather to financial market outcomes focus on how weather affects market participants' mood and beliefs. Instead, our paper aims to document how temperature exposures affect companies' actual earnings. Our focus on the cash flow channel is important, in that it allows us to further establish and understand the real economic effects of weather and climate.

2. Research design and methodology

2.1. Hypothesis development

Our main hypotheses are based on the idea that temperature extremes, through their effects on productivity and output, are likely to affect the profitability of the U.S. corporate sector. Jones and Olken (2010) and Dell et al. (2012) examine the negative impacts of climate shocks on GDP and exports across a large sample of countries. They suggest two channels through which climate shocks affect economic output: 1) agriculture and food-related industries that are sensitive to temperature extremes, and 2) decreased labor supply amid extremely high temperatures, especially in industries with high climate exposure (e.g., light manufacturing).

While the first channel is consistent with most people's expectations and the focus of much research in climate economics, the second is consistent with the age-old idea that laborers are less productive when temperatures are extremely high (Huntington, 1915). Linking the American Time Use Survey to regional weather data, Graff-Zivin and Neidell (2014) find that hot temperatures reduce hours worked in industries with high climate exposure.[5] This leads to our first set of hypotheses:

Hypothesis 1a: Greater exposure to extremely high temperatures will result in lower earnings for firms in agriculture-related industries, especially when shocks coincide with the sensitive crop growth season. and

Hypothesis 1b: Greater exposure to extreme temperatures will result in abnormal earnings for firms in industries with high labor productivity-based climate sensitivity.

Next, we aim to understand how quickly analysts and investors respond to intra-quarter extreme weather events for industries where we find that exposure to such events matters. In an efficient market, stock prices and analysts' earnings forecasts should adjust quickly to extreme weather events. In an international setting, Hong et al. (2019) show that food stock investors fail to efficiently discount the risks of droughts, generating predictable patterns in returns. Based on U.S. value and size portfolio returns as well as international data, Bansal et al. (2016a,b) show that stock returns incorporate temperature-induced disaster risks, consistent with predictions of a long-run risks model. Motivated by these recent studies, we examine whether stock prices and analysts' earnings forecasts reflect climate risks, as measured by firms' exposure to intra-quarter temperature extremes. This leads to our second hypothesis:

[4] An important caveat is that the effects we document, which speak to realizations from a particular weather distribution, could be very different from the effects associated with a distributional shift toward more extreme realizations. For example, firms might invest in more efficient heating and cooling equipment as extreme temperatures increase in frequency. While our study does not make out-of-sample projections, we do examine and find in-sample evidence of such adaptations. See Section 3.2.4.

[5] Using National Institute for Occupational Safety and Health definitions of heat exposed industries, Graff-Zivin and Neidell (2014) separate industries into high vs. low climate exposure categories. High climate exposure industries are those where the work is primarily performed outdoors (agriculture, forestry, fishing, hunting, construction, mining, and transportation and utilities) and manufacturing where facilities are not climate-controlled and the production process usually produces heat. The remaining industries are considered to have low climate exposure.

Hypothesis 2: Among firms in industries with temperature-sensitive earnings, stock prices adjust quickly and fully following intra-quarter exposure to extreme temperatures. Also, for such firms, analysts adjust their earnings forecasts quickly and fully following intra-quarter exposure to extreme temperatures.

Our empirical tests focus on these hypotheses, with the overall goal of understanding how extreme temperatures affect firms' earnings, analysts' earnings forecasts, and stock prices.

2.2. Data description and sample construction

Our analysis is based on the conjecture that temperature extremes, through their effects on productivity and output, are likely to affect the profitability of the U.S. corporate sector. The effects associated with extreme temperatures are likely to vary on several important dimensions. First, these effects are likely to vary substantially across industries and time. For example, it may be the case that extremely hot summer temperatures affect the output and profitability of firms with key inputs such as food crops and tobacco, but do not affect the profitability of airlines. In contrast, extremely cold winter temperatures, through their effects on overall air traffic and potential weather-related delays, may impact the profitability of airlines, while agriculture-related firms are likely to go unaffected.

Given this consideration, we conduct our analysis of the relationship between temperature extremes and corporate profitability on industry-by-season subsamples. In particular, we use the 68 Global Industry Classification Standard (GICS) six-digit industry classifications to construct subsamples for modeling this relationship.[6] Further, within each industry, we separately estimate the relationship between temperature extremes and profitability during each calendar quarter.

Because weather is location-specific, we account for firms' geographic footprints by obtaining establishment-level data from the National Establishment Time Series (NETS) Publicly Listed Database produced by Wall & Associates. This database provides addresses for each U.S. establishment owned by a public firm over the period from 1990 to 2015. Importantly, the database is free of survivorship bias, and contains information on over 1.45 million establishments over the sample period. In addition to locations, the database provides information on the portion of a firms' annual sales attributable to each of its establishments, as well as the number of employees working at each location. This allows us to track the economic importance of a firm's establishments in the cross-section.[7]

As in Addoum et al. (2020), Fig. 1 displays the establishment locations owned by all publicly traded U.S. firms in our sample during the sample period. Fig. 2 plots these locations for firms within each of the 10 GICS sectors. Both figures demonstrate the extensive geographic coverage of establishments in the NETS database.

Despite the extensive geographic coverage in the NETS data, it is important to mention a caveat that comes with its use relative to restricted-access administrative datasets. In particular, Crane and Decker (2020) conduct a comparison between NETS and the Census Bureau's Longitudinal Business Database (LBD) and Business Dynamics Statistics (BDS) datasets. They find that a large proportion of NETS sales and employment data are imputed and conclude that NETS appears ill suited for the study of labor market dynamics and firms entry and exit decisions. However, while Crane and Decker caution against using NETS for studying establishment and business growth, they also find that NETS is reasonably representative of U.S. business activity in the static cross-section. Importantly, this is exactly the dimension on which we rely upon NETS. In particular, we require a measure of the relative importance of a firm's business establishments in order to compute a firm-level temperature exposure measure weighted across the firm's geographic footprint. To the extent that NETS establishment-level sales and employment numbers are imputed and measured with error, this would introduce measurement error and attenuation bias, working against us finding significant results. Thus, the findings of Crane and Decker suggest that our results represent a lower bound for the effects of extreme temperatures.

Our use of the NETS data also comes with a distinct advantage relative to administrative data sources, where access is restricted to a small set of academic researchers and federal reserve employees. Namely, the LBD data to which Crane and Decker compare NETS are not publicly available to all researchers and the broader community with a potential interest in understanding the effects of extreme temperatures on corporate profitability. Our approach demonstrates the importance of extreme temperatures using data sources and methodology that can be applied and extended by a wide set of academic researchers and industry practitioners, rather than only those with restricted access.

To measure location-specific weather exposure, we obtain daily temperature and precipitation data from the PRISM Climate Group, which is the U.S. Department of Agriculture's official climatological database. The PRISM data capture the daily mean, minimum, and maximum temperature, as well as level of precipitation, in each of 481,631 16-square-kilometer (i.e., 4×4km) grids covering the continental United States. As in Addoum et al. (2020), Fig. 3 presents an example of the grids for Tompkins County, NY.

[6] This choice is guided by the evidence of Bhojraj et al. (2003), who show that among various industry classification schemes, GICS classifications are best at capturing common cross-sectional firm characteristics and comovement in stock returns.

[7] A limitation of our temperature exposure measure is that it captures only temperature shocks experienced at firms' U.S.-based operations. Since many firms have foreign revenue and cost centers, our measure may only partially capture the effects of temperature on earnings. We address this issue using data on firms' geographic financial segments. Specifically, FASB (Financial Accounting Standards Board) 14 and FASB 131 require public business enterprises to report financial and descriptive information about their operating segments. These also establish standards for related disclosures about, among other items, geographic areas. Compustat collects and reports this information in its Geographic Segment Files, allowing us to control for firms' foreign earnings exposures.

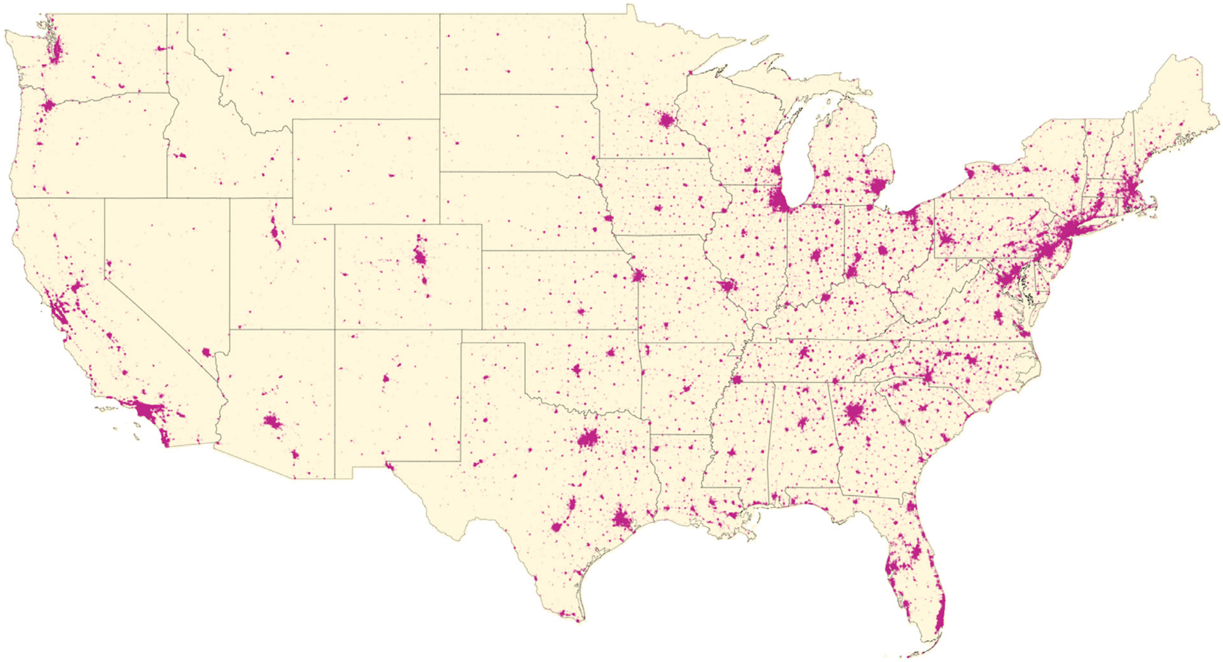

Fig. 1. Establishment Locations for U.S. Publicly Listed Firms. The figure plots the locations of 1.45 million establishments owned by all publicly traded U.S. firms. Establishment locations are obtained from the NETS Publicly Listed Database produced by Wall & Associates. The sample period is 1990 to 2015.

We compute the exposure to 1°C temperature bins varying from −15 to 50°C for each grid point, closely following the approach of Schlenker and Roberts (2009). Specifically, we fit a double sine curve passing through the minimum and maximum temperatures on consecutive days. We then aggregate the number of hours spent in a given temperature bin in each grid location during each month from 1990 to 2015.[8] As in Addoum et al. (2020), Fig. 4 illustrates the grid-level temperature exposure data. Panel A displays grid-level exposures (in hours) to temperatures above 30°C across the United States in July of 1999. Panel B presents grid-level exposures relative to the historical mean number of hours spent above 30°C in July.[9] While the plot in Panel A demonstrates significant geographic variation in temperature exposures, the figure in Panel B reveals important time series variation in temperatures relative to historical weather distributions.

We match the PRISM-based temperature exposure and geographic footprint data to construct a quarterly firm-level temperature exposure variable. First, we verify the geographic coordinates of each firm establishment location address using Google Maps. We then match these coordinates to a specific 4×4km PRISM bin to capture temperature exposure at a given establishment in a given month. Finally, we calculate the sales-weighted average exposure in each temperature bin across each firm's establishment locations in a given month.[10]

Next, we calculate each firm's temperature exposures across its establishment locations over each fiscal quarter in the sample. This is accomplished by aggregating the monthly exposures over each three-month interval representing a firm's fiscal quarters. For example, for a firm with fiscal quarter ending on March 31st, we aggregate monthly firm-level temperature exposures over January, February, and March. Similarly, for a firm with fiscal quarter ending on April 30th, we aggregate the temperature exposures over February, March, and April, and so on.

We also combine the PRISM precipitation data with the NETS locations in a similar way to the temperature bins. Specifically, we match the gridded monthly precipitation data to each establishment's geographic coordinates. We

[8] Though the temperature data are available beginning in 1981, our data on establishment locations begin in 1990.

[9] PRISM uses all available weather station data to calculate daily temperature and precipitation measures. As a result, some of the time series variation in these measures may stem from weather stations going in and out of existence. To account for this possibility, we recalculate our temperature exposure measures using the analogue of the PRISM daily weather data that keeps weather stations constant over time (available from Wolfram Schlenker's website: http://www.columbia.edu/~ws2162/dailyData.html). We find that the temperature exposures calculated using the PRISM data used in our baseline tests and those using this alternative data are very highly correlated. For example, the quarterly exposures to temperatures above 30°C (below 0°C) calculated using the two data sources for firms in our sample have an estimated correlation coefficient of 0.9949 (0.9977). Furthermore, we re-run our baseline earnings specifications and find that the results are essentially identical.

[10] As a robustness check, we verify the consistency of our results using different weighting schemes. We find qualitatively consistent results using weights based on number of employees across establishments and equal weights. Importantly, results with equal weights are somewhat less pronounced than with sales and employee weights, consistent with equal weights introducing attenuation bias induced by error in the measurement of each establishment's economic importance. See Appendix Tables A.1 and A.2.

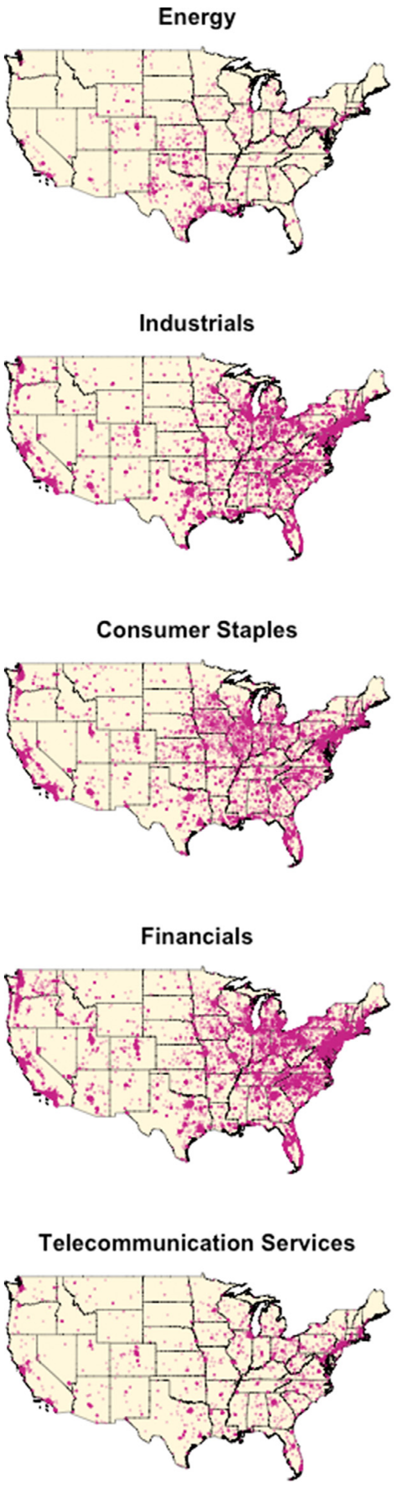

Fig. 2. Establishment Locations for U.S. Publicly Listed Firms, By GICS Sector. The figure plots the locations of establishments owned by all publicly traded U.S. firms within each of the 10 GICS sectors. Establishment locations are obtained from the NETS Publicly Listed Database produced by Wall & Associates. The sample period is 1990 to 2015.

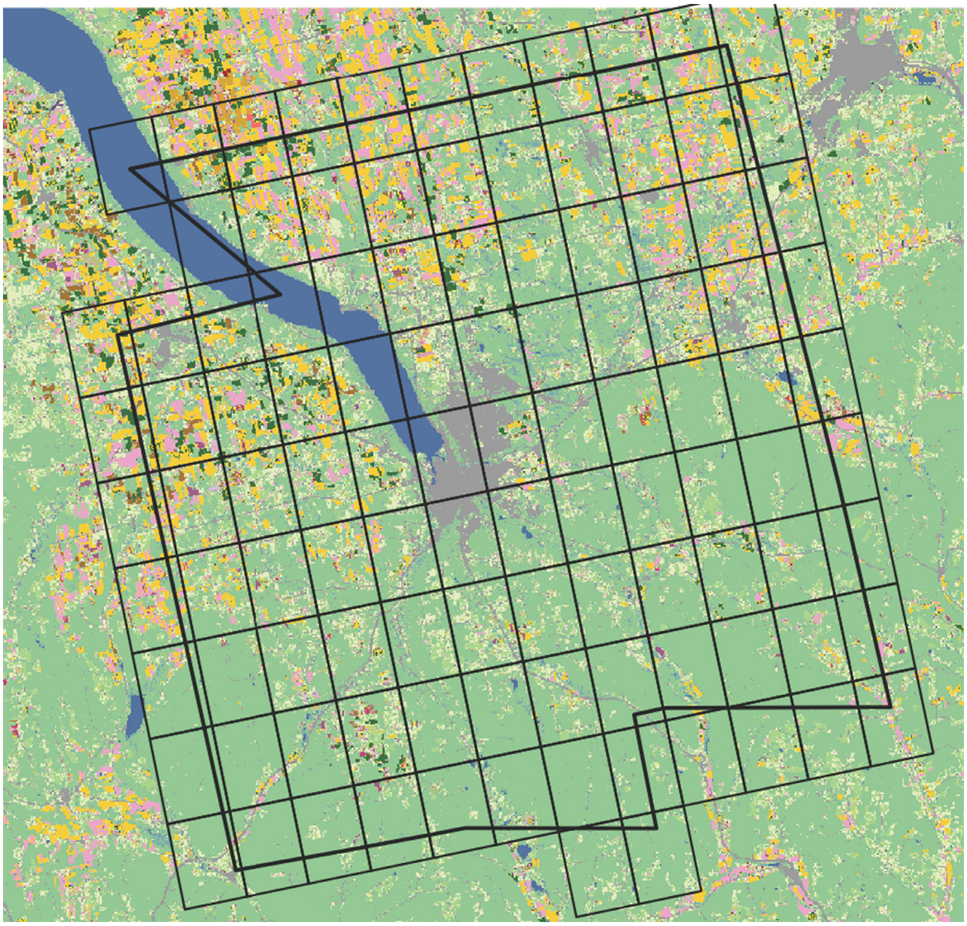

Fig. 3. PRISM Weather Grids. The figure overlays a map of Tompkins County, NY (1,274 sq. km) with a 4×4km grid corresponding to weather data. The grids and weather data are obtained from the PRISM Climate Group at Oregon State University. Daily grid-level data on minimum, maximum, and mean temperature from 1981–2015 are available from http://prism.oregonstate.edu.

then compute a sales-weighted average precipitation variable. Finally, we aggregate the monthly precipitation variable over three-month intervals matching each firm's fiscal quarters.

In order to analyze how expectations change as a result of extreme weather events, we collect split-adjusted quarterly earnings per share (EPS) information from the Thomson Reuters IBES database. To examine the channels through which extreme weather affects earnings, we further collect data on quarterly revenues, cost of goods sold (COGS), and selling, general, and administrative expenses (SG&A) from Compustat. We also compute quarterly operating costs as the sum of COGS and SG&A expenses. For comparability with the EPS data, we calculate split-adjusted per share values, scaled by beginning-of-quarter share price, for each of the Compustat variables.[11] Finally, we obtain data on common stock prices and returns for firms trading on the AMEX, Nasdaq, and NYSE exchanges from CRSP.

Table 1 reports summary statistics for key variables in the matched sample of financial and weather exposure variables. The top panel shows the mean, standard deviation, median, and first and third quartiles of each of the financial variables in our sample of firms. The bottom panels show the summary statistics for temperature, hours spent above 30°C and below 0°C, and precipitation experienced by sample firms during each quarter of the year.

[11] Note that the NETS data include establishments related to retail, wholesale, production, storage, and administrative functions, among others. Thus, in some industries, NETS establishment locations would be more likely to capture where production occurs rather than where sales are generated. For example, in manufacturing other industries where the location of production and sales can be very different, our temperature exposure measure would be more likely to capture supply-side effects associated with labor productivity and costs of production rather than demand effects. In contrast, for consumer sectors where establishments are naturally close to customers, the profitability effects of temperature extremes are more likely to be driven by consumer demand shifts. Importantly, our combination of Compustat/IBES and NETS data allows us to examine the heterogeneity across industries and understand the relative importance of these different channels. We do not take an a priori stance on which channel is likely to be of greatest importance, but instead use these potential channels as motivation for our main and auxiliary tests.

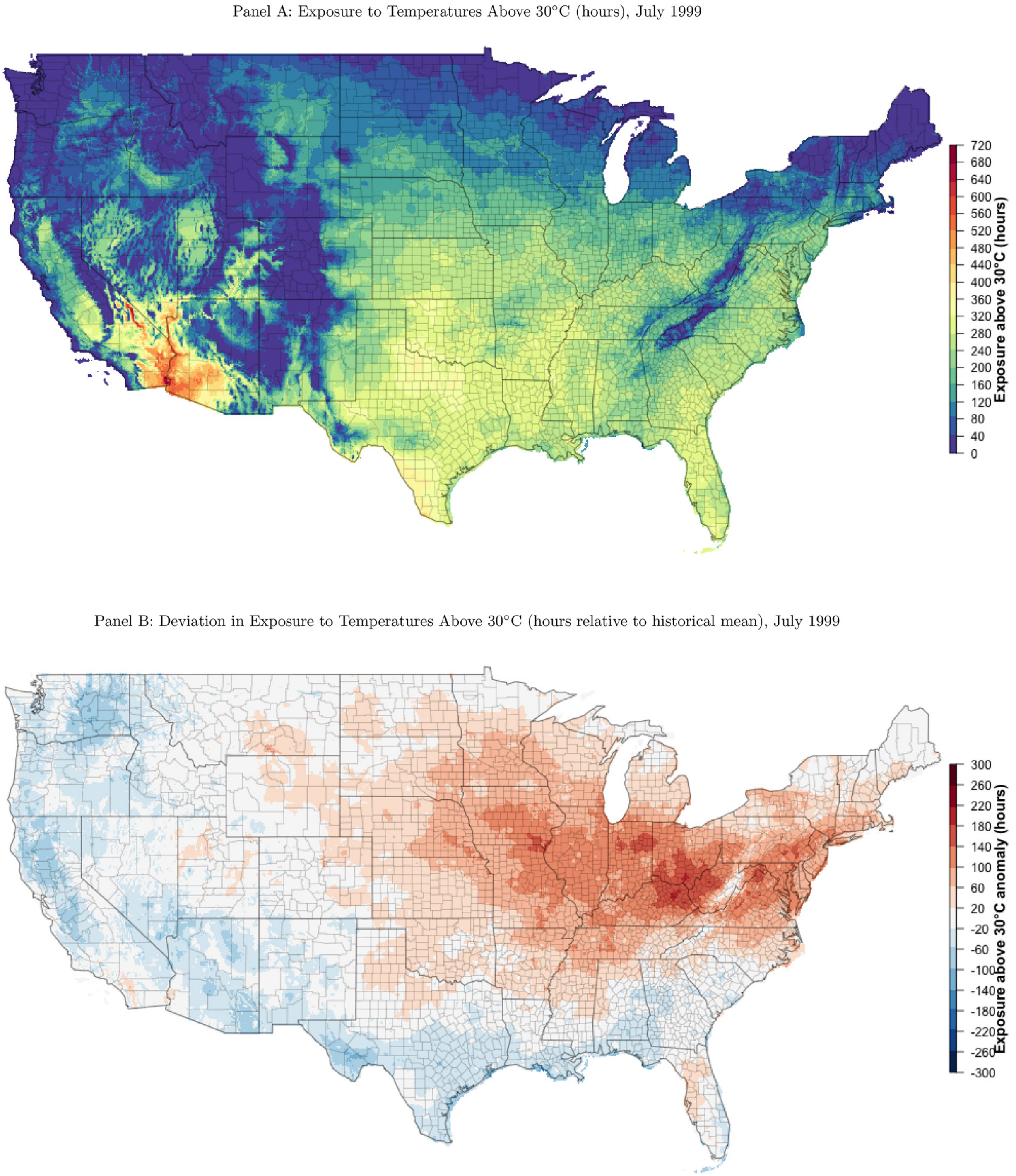

Fig. 4. Grid-level Exposure to Temperatures Above 30°C. The figure plots the exposure to temperatures above 30°C for 4×4km grids across the continental United States. In Panel A, the exposures are measured as the number of hours that the temperature exceeded 30°C during the month of July 1999. In Panel B, the exposures are measured as the deviation, relative to the historical mean, in the number of hours that the temperature exceeded 30°C during the month of July 1999. This information was derived from daily observations assuming a time-path following a double-sine curve passing through the minimum and maximum temperature of consecutive days (Schlenker and Roberts, 2009). Grid-level temperature data are obtained from the PRISM Climate Group at Oregon State University.

Table 1

Summary Statistics. This table reports summary statistics for key variables in the sample of matched quarterly financial and weather variables. Earnings per share (EPS) is the split-adjusted quarterly IBES actuals value scaled by the beginning-of-quarter share price. Operating costs are calculated as the sum of cost of goods sold (COGS) and selling, general, and administrative (SG&A) expenses. Revenues, operating costs, COGS, and SG&A expenses are all stated in split-adjusted per share terms and scaled by the beginning-of-quarter share price. Size is calculated as the log of total assets. Market-to-book is calculated as the sum of the market value of equity and book value of liabilities (total assets minus book equity) scaled by the book value of equity (total assets minus liabilities). Book leverage is calculated as the sum of short- and long-term liabilities scaled by total assets. The loss indicator is equal to one when Earnings is negative and zero otherwise. Dividend Yield is calculated as the sum of dividends paid over the preceding 12 months scaled by book equity. The no dividend indicator is equal to one when Dividend Yield is equal to zero and zero otherwise. Temperatures are reported in degrees Celsius and precipitation is reported in millimeters.

	Mean	Std. Dev.	1st Quartile	Median	3rd Quartile
Financial Variables					
Earnings per share (EPS)	0.007	0.033	0.005	0.012	0.019
Revenues	0.305	0.689	0.046	0.154	0.357
Operating Costs	0.245	0.601	0.032	0.111	0.283
Cost of Goods Sold	0.195	0.501	0.016	0.078	0.225
SG&A Expenses	0.044	0.127	0.000	0.022	0.056
EPS, Mean Forecast	0.008	0.025	0.005	0.012	0.018
SUE	−0.001	0.015	−0.001	0.000	0.002
Log Assets	5.885	2.141	4.354	5.889	7.323
Market-to-Book	1.515	1.603	0.676	1.041	1.718
Book Leverage	0.228	0.213	0.037	0.182	0.359
Loss Indicator	0.228	0.42	0	0	0
Dividend Yield	0.026	0.056	0.000	0.000	0.031
No Dividend Indicator	0.555	0.497	0	1	1
Firm-quarter Weather Variables, by calendar quarter					
Quarter 1 - Winter					
Max Temp	10.8	5.8	6.4	10.2	15.3
Mean Temp	5.5	5.6	1.5	5.0	9.7
Min Temp	0.3	5.4	−3.5	−0.2	4.1
Hours above 30C	2.0	6.3	0.0	0.0	1.2
Hours below 0C	576.5	434.7	191.8	550.1	879.4
Precipitation	230.0	105.0	161.4	221.1	288.1
Quarter 2 - Spring					
Max Temp	22.5	4.5	20.4	22.7	25.2
Mean Temp	16.7	4.4	14.7	16.9	19.2
Min Temp	10.9	4.4	8.8	11.2	13.4
Hours above 30C	119.5	128.2	30.3	79.1	161.1
Hours below 0C	54.1	129.7	0.0	8.3	36.5
Precipitation	253.8	123.1	180.8	255.8	327.7
Quarter 3 - Summer					
Max Temp	28.7	2.9	26.8	28.5	30.4
Mean Temp	23.0	2.8	21.1	22.7	24.5
Min Temp	17.2	3.0	15.2	17.0	19.0
Hours above 30C	344.5	265.6	146.0	279.0	474.4
Hours below 0C	0.3	2.4	0.0	0.0	0.0
Precipitation	249.4	145.9	160.6	252.5	332.1
Quarter 4 - Autumn					
Max Temp	16.7	5.5	12.4	16.0	20.6
Mean Temp	11.3	5.2	7.4	10.5	14.8
Min Temp	5.9	5.1	2.3	5.1	9.2
Hours above 30C	42.5	89.2	0.0	10.5	41.7
Hours below 0C	239.8	238.9	29.0	184.2	371.3
Precipitation	235.5	115.2	159.2	230.0	299.0

There are clear seasonal effects across quarters. Quarters 1 (winter) and 4 (autumn) are associated with lower mean temperatures (5.5°C and 11.3°C) compared to quarters 2 (spring) and 3 (summer) (16.7°C and 23.0°C). Firms spend a considerable number of hours (550 hours at the median) below freezing in quarter 1. During the summer months of quarter 3, the median firm spends a large amount of time (279 hours) above 30°C.

2.3. Estimation methodology

To test the relationship between extreme temperatures and firm profitability, we estimate regressions of firm profitability on the temperature exposure measure. Following the climate impact literature closely (e.g. Schlenker and Roberts, 2009; Burke et al., 2015; Blanc and Schlenker, 2017), we assume that firm-level earnings depend on temperature, denoted by h, across a firm's establishments. Further, we assume that temperature ef-

Table 2
Quarterly Sensitivity of Industry Earnings to Extreme Cold and Heat. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), with coefficients reported in Internet Appendix Table IA1 and associated earnings response functions displayed in Fig. 5. We focus on industries with a statistically significant relation between earnings and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (+,−10°) Software (−, −5°)	Leisure Products (+,−10°) Textile, Apparel & Lux. (−, 2°) Hotels & Restuarants (−, 4°) Beverages (−, 8°) Personal Products (−, 1°) Pharmaceuticals (−, 6°) Life Science Tools (+,0°)	Leisure Products (+,9°) Health Care Equip. (+,11°) Electric Utilities (−, 13°)	Oil, Gas & Fuels (+,−4°) Specialty Retail (+,5°) IT Services (−, −11°) Software (−, −2°)
Heat Shock Sensitivity	Trading Cos. & Distrib. (+,27°) Comm. Serv. & Supplies (+,23°) Electric Utilities (−, 19°)	Construction Materials (+,30°) Leisure Products (−, 37°) Personal Products (+,30°) Health Care Equip. (+,29°) Multi-Utilities (+,30°)	Construction & Eng. (−, 32°) Leisure Products (−, 37°) Capital Markets (−, 37°) Gas Utilities (−, 34°) Electric Utilities (+,32°)	Metals & Mining (+,28°) Machinery (−, 28°) Airlines (+,24°) Capital Markets (+,25°)

fects are time-separable and potentially non-linear within quarters.[12]

Specifically, we posit the following form for the earnings process in each calendar quarter:

$$EPS_{i,j,t} = \alpha_i + \delta_t + \int_{\underline{h}}^{\overline{h}} g_j(h)\phi_{i,t}(h)dh + \Gamma X_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $EPS_{i,j}$ measures the split-adjusted earnings per share (scaled by beginning-of-quarter share price) of firm i in industry j and $\phi_i(h)$ is the sales-weighted time distribution of heat in firm i's establishment locations. Observed temperatures over quarter t are assumed to vary between lower bound $\underline{h}$ and upper bound $\overline{h}$. Finally, $X_{i,t-1}$ is a vector of firm-specific lagged control variables as well as linear and quadratic precipitation variables. Following Fama and French (2000), the set of control variables includes firm size, market-to-book ratio, book leverage, an indicator for a loss in the previous quarter, dividend yield over the previous 12 months, and a no-dividend indicator. We also include linear and quadratic precipitation variables that measure the sales-weighted precipitation in firm i's establishment locations. Importantly, we include firm and time fixed effects, respectively captured by α_i and δ_t, which allow us to identify the nonlinear effects of temperature using random and exogenous variation in the distribution of heat around each firm's mean (Blanc and Schlenker, 2017).[13]

Empirically estimating the process in Eq. (1) requires specification of a functional form for $g_j(h)$, a function mapping a marginal unit of time exposure at each temperature h to profitability among firms in industry j. We assume each $g_j(h)$ follows a third-order Chebyshev polynomial such that $g_j(h) = \sum_{k=1}^{3} \gamma_{j,k} T_k(h)$, where T_k is the kth order Chebyshev polynomial.[14]

We approximate the integrals above by using data on exposures to each 1°C temperature bin, evaluating $g_j(h)$ at the midpoint. We then estimate predictive regressions as follows:

$$EPS_{i,j,t} = \alpha_i + \delta_t + \sum_{\underline{h}}^{\overline{h}} \sum_{k=1}^{3} \gamma_{j,k} T_k(h+0.5)[\Phi_{i,t}(h+1) - \Phi_{i,t}(h)] + \Gamma X_{i,t-1} + \varepsilon_{i,t}. \quad (2)$$

We transform the dependent variable by taking the log of one plus EPS to aid in interpretation of estimated coefficients. To ensure the stability of the non-linear temperature exposure effects, we determine $\underline{h}$ and $\overline{h}$ endogenously. In particular, we top- and bottom-code each tail of the observed temperature distribution so that the highest and lowest temperature bins have at least 0.5% exposure over the sample.

Temperature exposure and precipitation are measured over the fiscal quarter in which earnings are generated (i.e., from time $t-1$ to t). First, it is important to note that this does not induce a look-ahead bias, since the PRISM weather grid data are available on a next-day basis. Second, this implies that weather-based measures potentially represent a more timely source of cash flow news relative to accounting-based variables that are available with a one-quarter lag.

[12] The time-separability assumption amounts to assuming that for a given firm-quarter observation, exposure to extreme temperatures has the same effect regardless of the point of exposure during the quarter. For example, a heat wave that leads to 5 days of exposure to temperatures above 35°C in May would have the same impact on earnings as an identical exposure in June.

[13] To the extent that the geographic footprints of firms in a given industry vary significantly, we can include time fixed effects. However, given the evidence that industries are geographically concentrated (e.g. Ellison and Glaeser, 1997; Ellison et al., 2010), it may be more appropriate to remove the time fixed effects for some industries. We explore the robustness of our results to their exclusion and find that the effects are qualitatively similar.

[14] Alternative choices for the functional form of $g_j(h)$ include a step function using indicator variables and a piecewise linear approximation. We conduct robustness tests using these alternatives, as well as for higher-order Chebyshev polynomials, and find that our results are qualitatively unchanged.

3. Empirical tests and results

3.1. Do temperature extremes represent cash flow news?

We begin by asking whether extreme temperature events across firms' establishment locations represent a timely source of cash flow news. In particular, are extreme temperature events within a quarter useful predictors of quarterly earnings? Importantly, we would like to understand whether the effects of temperature exposure are confined to agricultural industries (*Hypothesis 1a*) and industries with high labor productivity-induced climate exposure (*Hypothesis 1b*), or whether the effects are more widespread.

Since the effects of temperature exposure are likely to vary across industries, we estimate Eq. (2) on GICs six-digit industry subsamples. Further, because these effects may vary by season even within a given industry, we also separately estimate the potentially nonlinear relationship between temperature exposure and firm profitability by calendar quarter.

We present analysis to this effect in Fig. 5. The figure plots estimated nonlinear relations between firm profitability and temperature bin exposures for industry-quarters with significant earnings sensitivity to extreme temperatures.[15] We also plot the frequency distribution across temperature bins over the sample period for each industry-quarter.

The estimates in Fig. 5 indicate that the profitability of over 40% (24 out of 59) of industries exhibit sensitivity to extreme temperatures. Table 2 summarizes the industries that exhibit earnings sensitivity with respect to extreme temperatures and also provides critical temperature thresholds below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings. The effects of temperature extremes apply to a wide range of industries. The sectors that are the most affected include consumer discretionary (leisure products; textiles, apparel and luxury goods; hotels and restaurants; beverages; and specialty retail), industrials (aerospace and defense; airlines; construction and engineering; and machinery), utilities (electric utilities; gas utilities; and multi-utilities) and health care (health care equipments; pharmaceuticals; and life science tools), among others.

Hot and cold temperature extremes affect this diverse set of industries in varying ways during different seasons. In particular, extremely hot summers and extremely cold spring temperatures tend to be bad news for earnings, while a warm autumn generally has a positive effect. Heat waves in the summer (Q3) are consistently bad for corporate earnings: four industries (construction and engineering; leisure products; gas utilities; and capital markets) report significantly lower corporate earnings. Extremely cold temperatures in spring (Q2) are also generally bad news for corporate earnings. Five industries, several of which are travel related (airlines; hotels and restaurants; beverages; textile, apparel, and luxury goods; and pharmaceuticals), have lower earnings, while two other industries (life science tools; and leisure products) have significantly higher earnings.

Meanwhile, warm autumn (Q1) extremes are generally good for corporate earnings: three industries (airlines; metals and mining; and capital markets) report significantly higher earnings, although one industry (machinery) reports lower earnings. Interestingly, the same industry can be affected by both extreme hot and cold temperatures. For instance, earnings for electric utilities are hurt by both extremely warm winter temperatures and cool summers, presumably because of lower heating and air conditioning use by consumers during the respective seasons.

Importantly, these temperature effects also appear to be economically important. In particular, in Appendix Table A.3, we consider the economic effects associated with a doubling of the extreme 5% tails of the temperature distribution experienced by firms in each industry.[16] We find that among the 32 industry-quarters with significant extreme temperature-earnings relations outlined in Table 2, the average overall impact of a doubling of extreme temperature frequencies implies a 37.4 basis point change in earnings. Among the set of 17 industry-quarter combinations with negative earnings responses, we find that a doubling of the 5% extreme temperature frequency implies a 28 basis point earnings decrease, on average. This effect is also important among the 15 industry-quarters for which extreme temperatures are associated with a positive impact on earnings, amounting to an average 48 basis point increase in profitability.

There are several important caveats to the temperature effects that we identify. First, a limitation of our temperature exposure measure is that it captures only temperature shocks experienced at firms' U.S.-based operations. Since many firms have foreign revenue and cost centers, our measure may only partially capture the effects of temperature on earnings. We address this issue by controlling for firms' foreign earnings exposures using data on their geographic financial segments. Second, the temperature effects we document are likely to be net of firms' hedging activities. While these net magnitudes are interesting in their own right, we also isolate the gross effect of extreme temperatures on corporate profitability net of firms' hedging potential. Specifically, we exploit the natural experiment setting of Purnanandam and Weagley (2016), in which the CME Group introduced city-specific weather derivative contracts in a staggered fashion. Finally, it may be the case that firms operating in relatively hotter areas of the U.S. exhibit industry temperature sensitivity that differs from those with geographic footprints concentrated in cooler regions of the country. We address this potential con-

[15] Throughout our analysis, we continue to focus on the set of industry-quarter combinations that exhibit statistically significant earnings sensitivity to extreme temperatures. However, we plot the full set of earnings response functions for each of 59 GICS six-digit industries over all calendar quarters (Q1-Q4) in Internet Appendix Figure IA1. We also report all corresponding regression coefficients and associated test statistics in Internet Appendix Table IA1.

[16] This is a conservative choice motivated by the findings of Lau and Nath (2012), who project that from 2000 to 2050, the frequency, duration, and number of heat wave days in various North American regions will increase by respective factors of 1.2–2.2, 2.2–3.8, and 2.9–5.1.

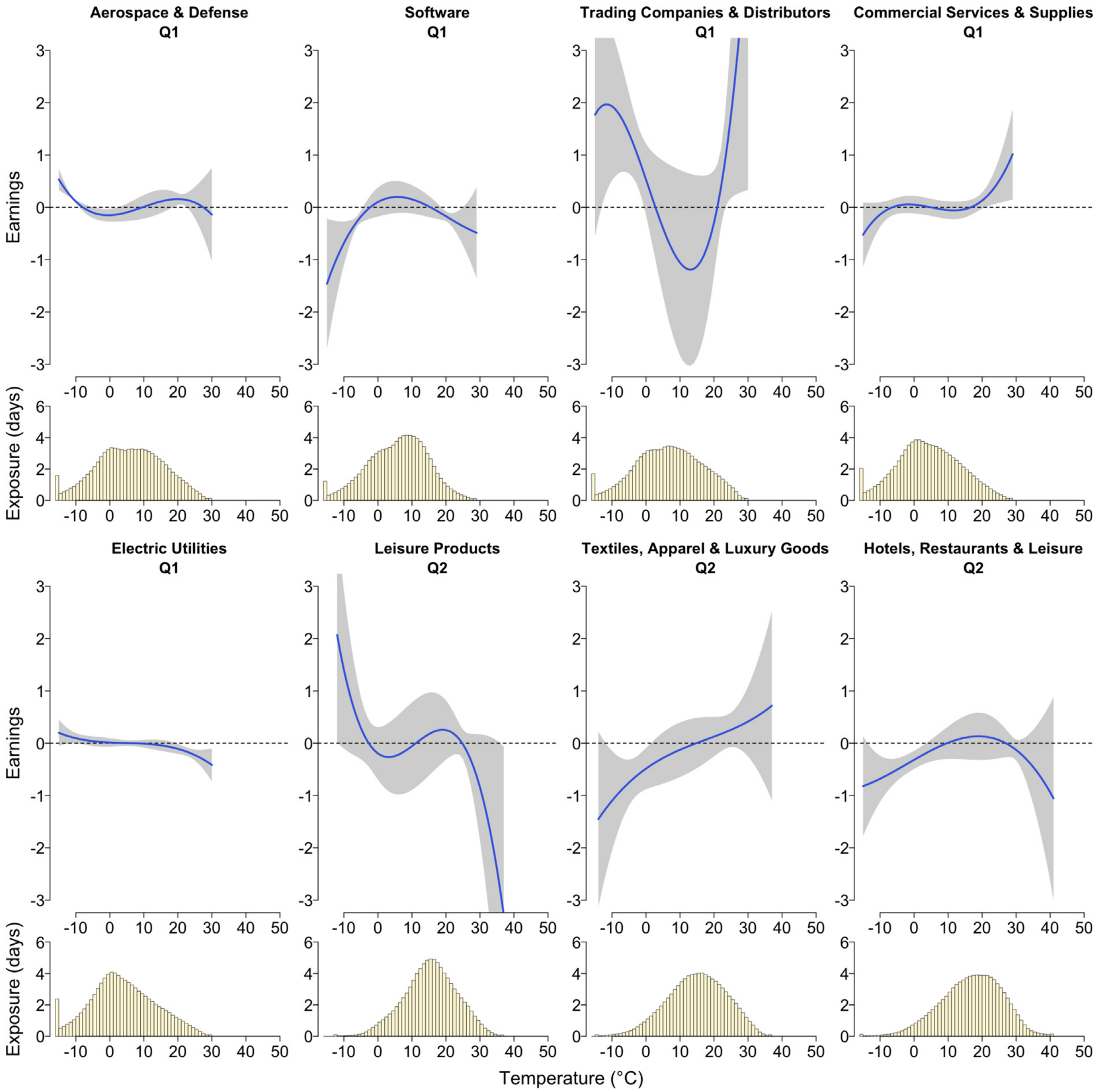

Fig. 5. Nonlinear Relations Between Firm Profitability and Temperature. The figure displays the nonlinear effects of temperature exposure on profitability based on regression specifications (Eq. (2)) estimated for fiscal quarters ending during each calendar quarter of the year (Q1-Q4). We plot estimated response functions surrounded by ±2 standard error bands. Standard errors are clustered by firm and quarter. Impacts (y-axis) are reported in log points multiplied by 1,000. Underlying regression coefficients are reported in Internet Appendix Table IA1. The bar plot distributions underneath each marginal effect plot illustrate the underlying distribution in temperature exposure for each 1°C temperature bin over the sample. Each panel focuses on a specific 6-digit GICS industry.

cern by splitting each industry subsample into north and south subsamples, based on the sales-weighted centroid of firms' establishment locations and test whether earnings-temperature relationships differ between firms with more north vs. south-based operations. Details of these robustness tests are presented in Appendix A.

3.1.1. Mechanisms driving temperature sensitivities

In an effort to understand the channels driving the effects of extreme temperature on profitability, we further investigate how exposure to extreme temperatures affects the revenue and operating cost components of earnings among companies in each industry. We assess whether revenues or operating costs are the dominant force driving the earnings-temperature relations we document. Generally, revenues and operating costs rise and fall together. However, positive or negative earnings effects occur when these fluctuations do not fully offset one another. For example, an industry that exhibits a positive relation be-

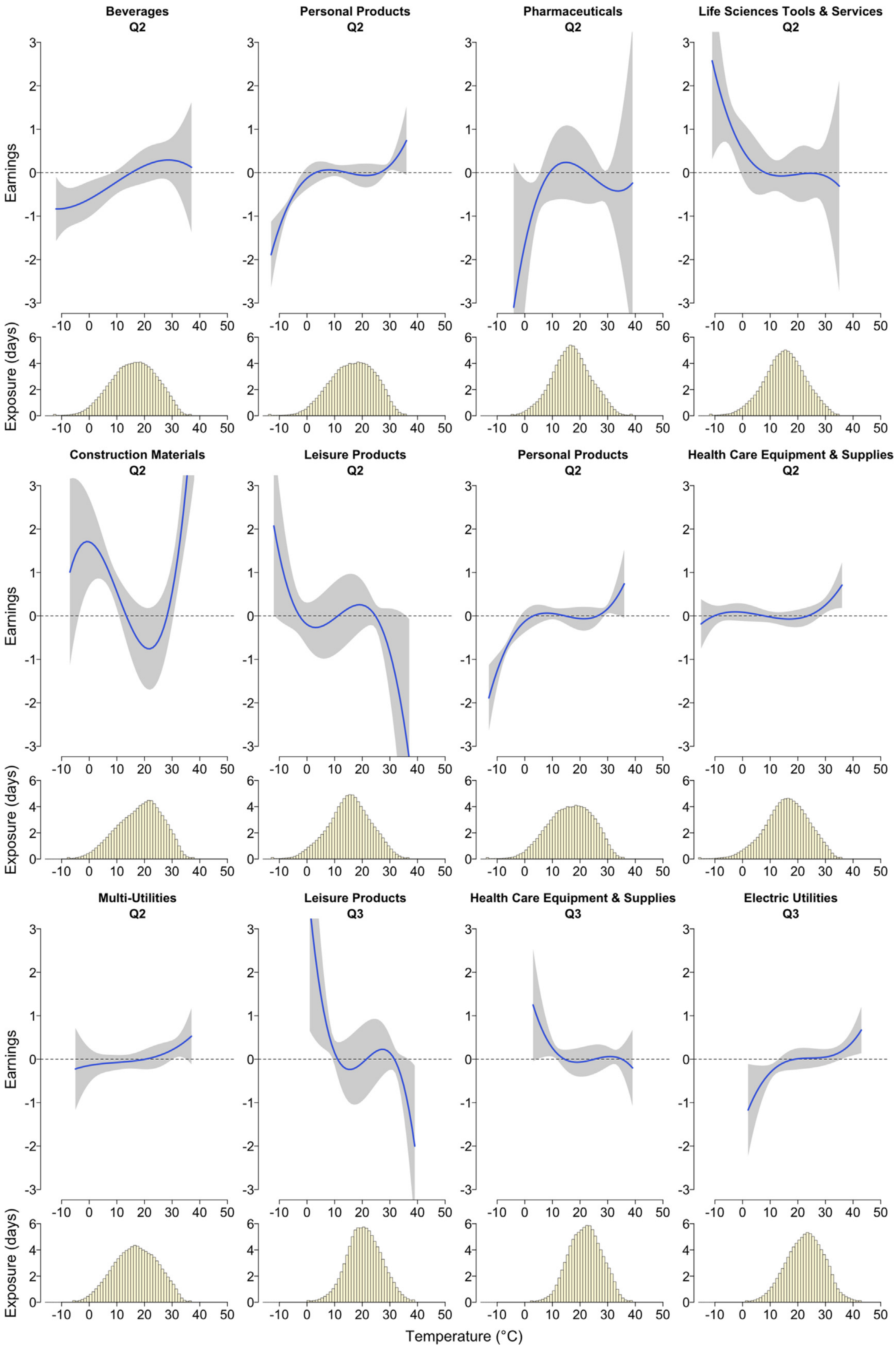

Fig. 5. Continued

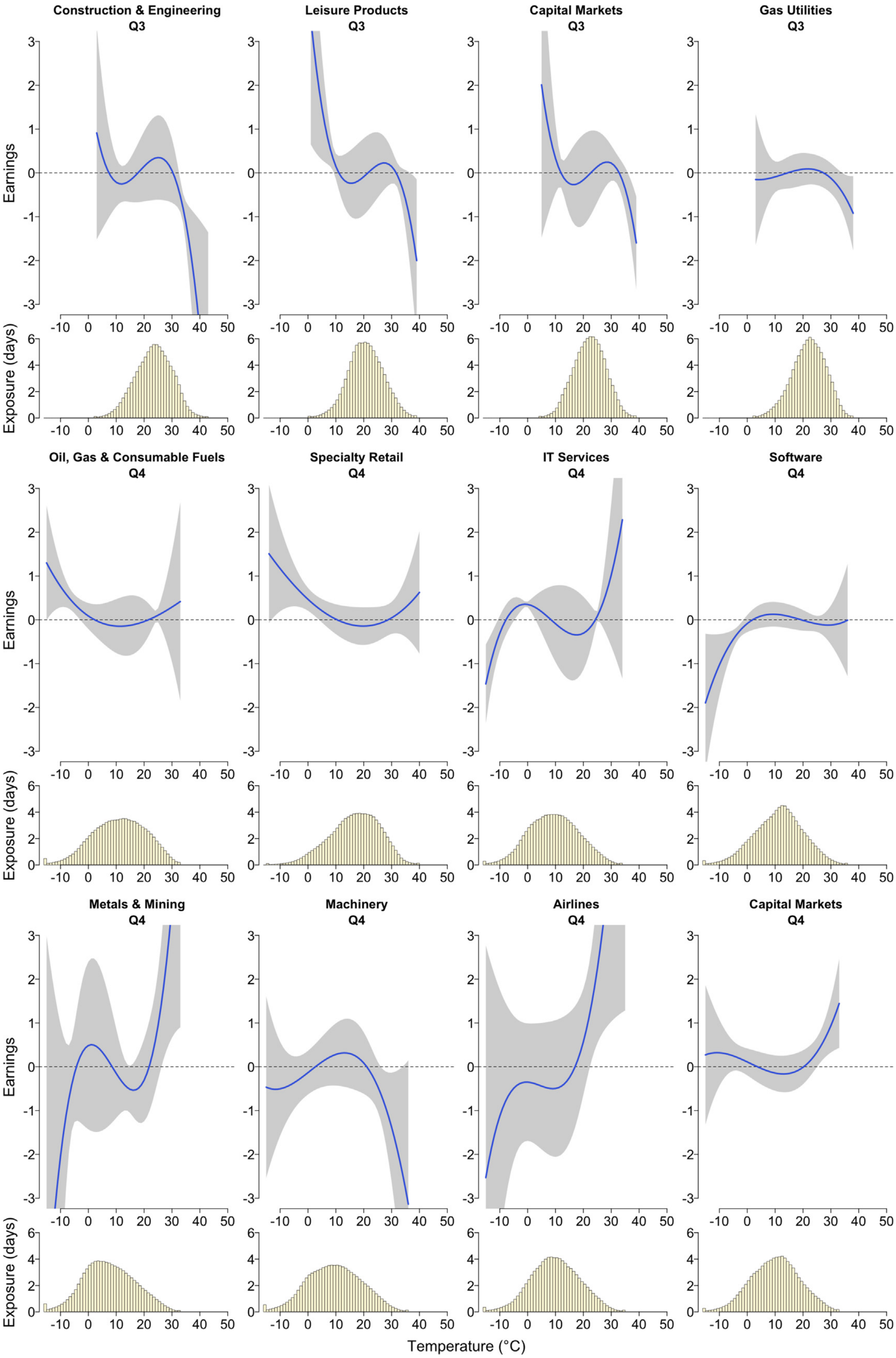

Fig. 5. Continued

Table 3
Quarterly Sensitivity of Industry Revenues and Operating Costs to Extreme Cold and Heat. This table reports directional effects for earnings, revenues, and operating costs among GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), with revenues and operating costs as the dependent variables and associated response functions displayed in Fig. 6. We focus on industries with a statistically significant relation between EPS and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) a given measure, while 0 indicates that extreme temperature exposure has approximately no effect. Earnings, revenues, and operating costs are respectively denoted by E, R, and C. For revenues and operating costs, * indicates that the effect of extreme temperature exposure is statistically significant at the 5% level.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (E+,R+*,C+*) Software (E−,R+,C+)	Leisure Products (E+,R+,C+) Textile, Apparel & Lux. (E−,R−,C−) Hotels & Restuarants (E−,R−,C−) Beverages (E−,R−,C−) Personal Products (E−,R−*,C−*) Pharmaceuticals (E−,R−*,C−*) Life Science Tools (E+,R−,C−)	Leisure Products (E+,R−,C−) Health Care Equip. (E+,R+,C+) Electric Utilities (E−,R−,C−)	Oil, Gas & Fuels (E+,R+,C+) Specialty Retail (E+,R+,C+) IT Services (E−,R−,C−) Software (E−,R+,C+)
Heat Shock Sensitivity	Trading Cos. & Distributors (E+,R−,C−) Commercial Serv. & Supplies (E+,R+,C+) Electric Utilities (E−,R+,C+)	Construction Materials (E+,R+*,C+*) Leisure Products (E−,R−,C−) Personal Products (E+,R+,C+) Health Care Equip. (E+,R−,C−) Multi-Utilities (E+,R+*,C+)	Construction & Eng. (E−,R−,C−) Leisure Products (E−,R0,C+) Capital Markets (E−,R−,C−) Gas Utilities (E−,R−*,C−*) Electric Utilities (E+,R0,C0)	Metals & Mining (E+,R+,C0) Machinery (E−,R−,C−) Airlines (E+,R+,C+) Capital Markets (E+,R+,C+)

tween extreme temperature exposure and earnings may do so because temperature shocks lead to higher revenues that are not fully offset by operating costs. However, the same positive temperature-earnings relation may result from operating cost savings that dominate economically smaller, or even nonexistent, revenue effects.

We dissect the impact of extreme temperatures on profitability into separate revenue and cost components and report the results in Table 3 and Fig. 6. We find that in most cases, revenue effects drive our profitability results. For example, during extremely hot summers, firms in the construction and engineering, capital markets, and gas utilities industries experience decreased revenues that are not fully offset by a reduction in operating costs, resulting in lower earnings. In a more limited number of cases, operating costs drive the profits. In particular, we find that extremely hot summer temperatures do not affect revenues among leisure products firms, but that increased operating costs affect profits negatively. Further, we find that cold spring temperatures lead to decreased revenues among life science tools firms, but that even larger decreases in operating costs generate a positive net effect on earnings.

In Table 4 and Fig. 7, we further break down the effects of extreme temperatures on operating costs into cost of goods sold (COGS) and selling, general, and administrative (SGA) components. This allows us to better understand the extent to which operating cost effects are associated with direct labor and material costs that are included in COGS, versus non-production costs that are included in SGA, such as electricity expenses associated with heating and cooling a firm's facilities. We find that, with few exceptions, operating cost effects are generally driven by COGS temperature sensitivity and not by effects associated with SGA. For example, the statistically significant increase in operating costs among aerospace and defense firms during cold winter months are driven by a significant increase in COGS. In contrast, SGA costs are not sensitive to cold temperature extremes, suggesting that only aerospace and defense firms' direct production costs are affected. Interestingly, five temperature-sensitive industries exhibit significant SGA sensitivity: personal products and pharmaceuticals in cold Q2 months, construction materials in hot Q2 months, IT services in cold Q4 months, and machinery in hot Q4 months. While some of these industries also have significant revenue and COGS temperature sensitivity, the earnings sensitivity of IT services and machinery firms is driven by SGA effects, suggesting that non-production costs such as heating and cooling are especially important in these industries.[17]

3.1.2. Discussion and hypothesis evaluation

To sum up our empirical results so far, we document an assortment of industries exhibiting significant earnings-temperature sensitivities and employ an array of tests aimed at understanding the channels that drive these relations. With respect to our first hypothesis, that extreme temperatures will affect profitability in agricultural and related industries (*Hypothesis 1a*), we do not find strong evidence that this agricultural channel significantly affects the

[17] We present additional exploratory tests related to both the heating/cooling and labor productivity channels in Appendix B.

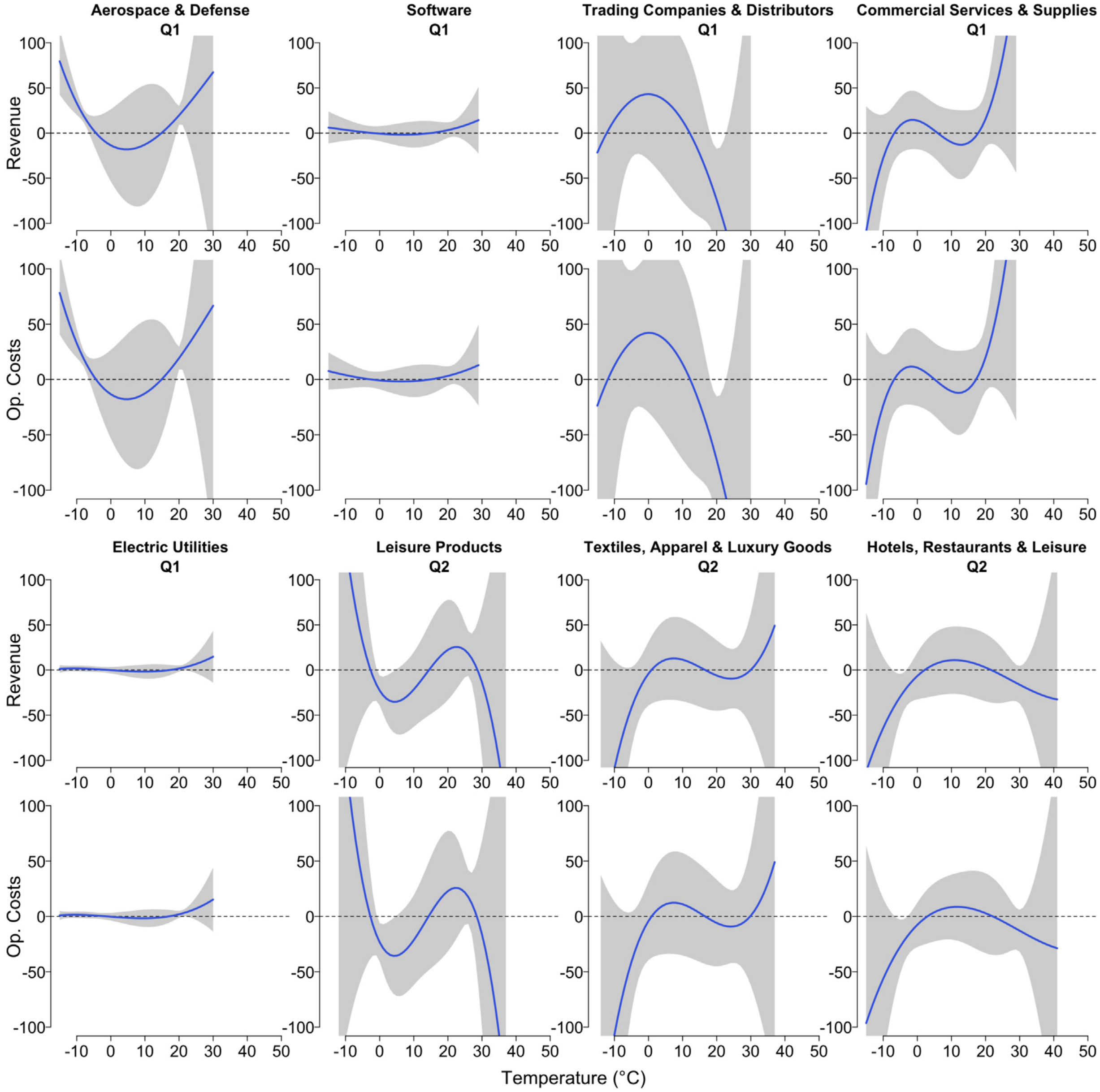

Fig. 6. Nonlinear Relations Between Firm Revenues, Operating Costs, and Temperature. The figure displays the nonlinear effects of temperature exposure on the revenue and operating cost components of earnings based on regression specifications (Eq. (2)) estimated for fiscal quarters ending during each calendar quarter of the year (Q1-Q4). We plot estimated response functions surrounded by ±2 standard error bands. Standard errors are clustered by firm and quarter. Impacts (*y*-axis) are reported in log points multiplied by 1,000. Each panel focuses on a specific 6-digit GICS industry and we restrict the analysis to industries where there are significant relations between temperature shocks and profitability (Fig. 5).

earnings of firms in our sample. This is likely due to our focus on publicly traded firms, a sample that includes very few companies directly involved in farming and agricultural production. Meanwhile, we also find no significant earnings-temperature relations among closely related industries such as food products (i.e., producers of agricultural products and packaged food and meat) and food and staples retailing (i.e. grocery stores). In contrast, we do find significant extreme temperature effects among firms in the beverages and hotels and restaurants industries. However, we also find that these earnings effects are driven by a revenue rather than a cost channel, suggesting that they may be more related to consumer demand than agricultural crop yields.

We find more support for the climate exposure channel related to labor productivity (*Hypothesis 1b*). Graff-Zivin and Neidell (2014) propose several industries likely to experience high climate exposure due to heat-induced labor productivity losses. We find that many of the industries where operating costs are the dominant channel driving earnings effects match up with those proposed by Graff-Zivin and Neidell. In particular, we find

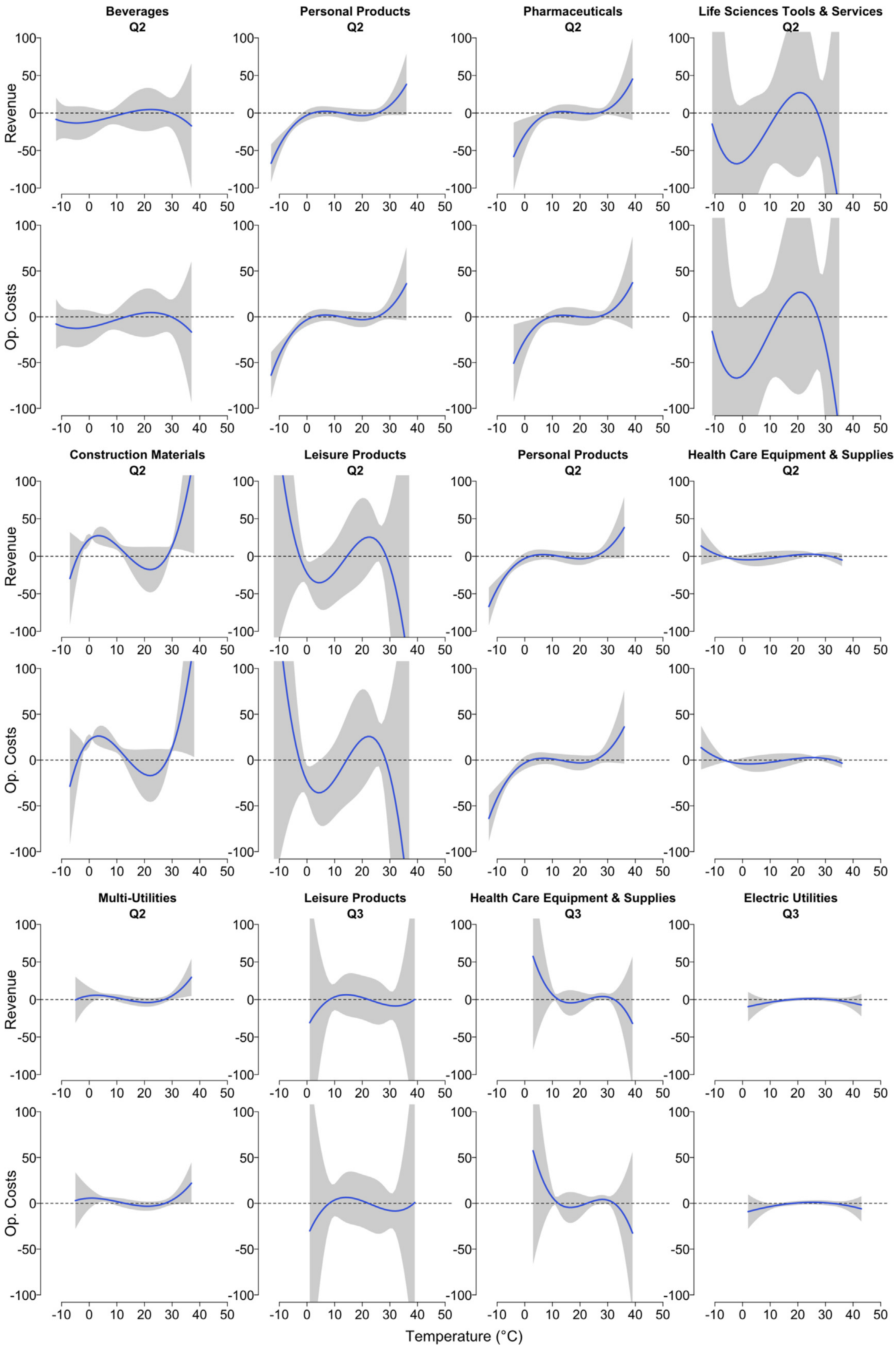

Fig. 6. Continued

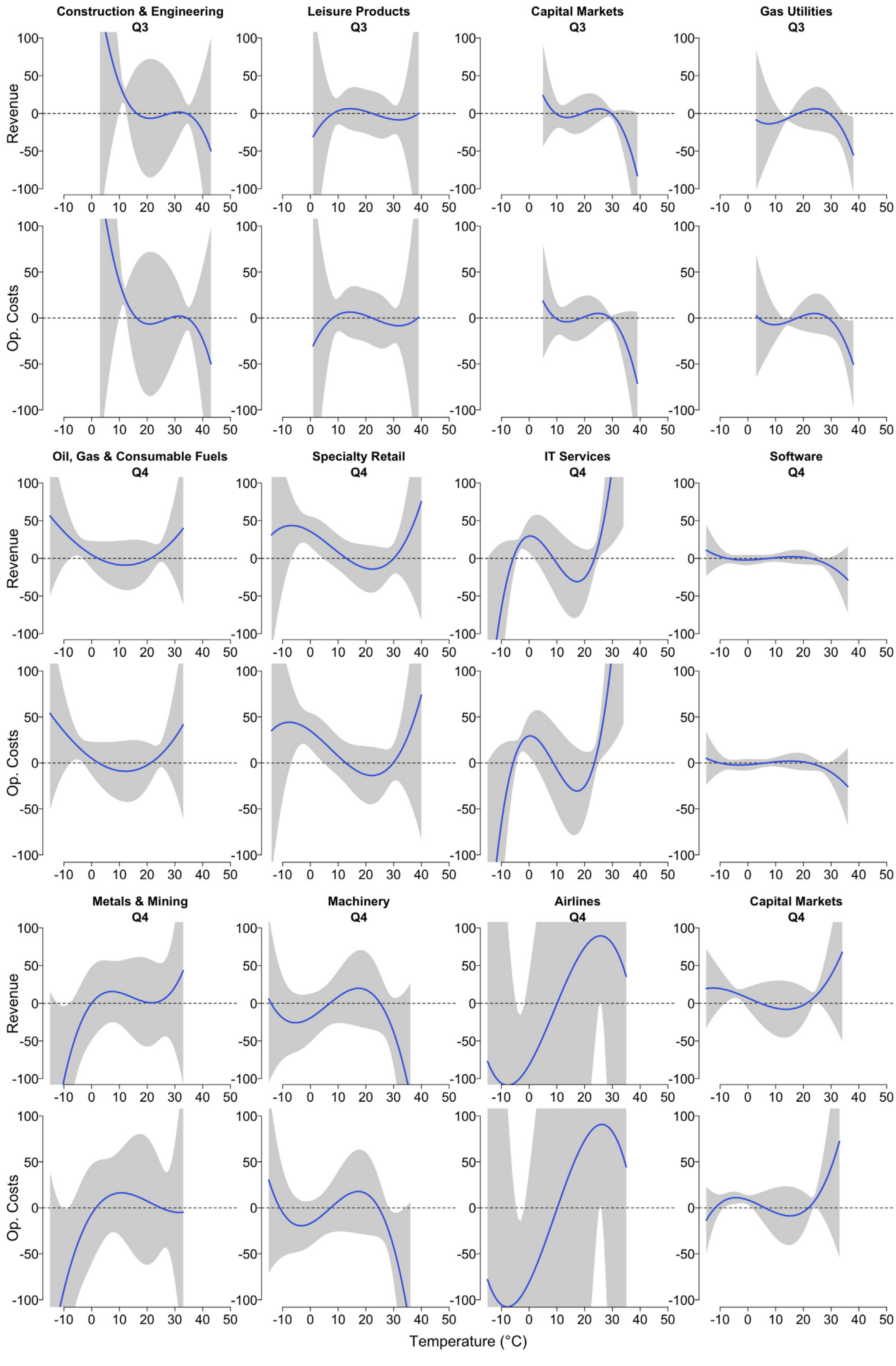

Fig. 6. Continued

Table 4
Quarterly Sensitivity of Industry Cost of Goods Sold and SG&A Expenses to Extreme Cold and Heat. This table reports directional effects for operating costs, cost of goods sold, and selling, general, and administrative (SG&A) expenses among GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), with cost of goods sold and SG&A expenses as the dependent variables and associated response functions displayed in Fig. 7. We focus on industries with a statistically significant relation between EPS and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) a given measure, while 0 indicates that extreme temperature exposure has approximately no effect. Operating costs, cost of goods sold, and SG&A costs are respectively denoted by C, COGS, and SGA. For all measures, * indicates that the effect of extreme temperature exposure is statistically significant at the 5% level.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (C+*,COGS+*,SGA0) Software (C+,COGS0,SGA0)	Leisure Products (C+,COGS+,SGA0) Textile, Apparel & Lux. (C−,COGS−,SGA0) Hotels & Restuarants (C−,COGS−,SGA0) Beverages (C−,COGS−,SGA0) Personal Products (C−*,COGS−*,SGA−*) Pharmaceuticals (C−*,COGS−*,SGA−*) Life Science Tools (C−,COGS0,SGA0)	Leisure Products (C−,COGS−,SGA0) Health Care Equip. (C+,COGS0,SGA0) Electric Utilities (C−,COGS−,SGA0)	Oil, Gas & Fuels (C+,COGS+,SGA0) Specialty Retail (C+,COGS+,SGA0) IT Services (C−,COGS−,SGA−*) Software (C+,COGS0,SGA0)
Heat Shock Sensitivity	Trading Cos. & Distributors (C−,COGS−,SGA0) Commercial Serv. & Supplies (C+,COGS+,SGA0) Electric Utilities (C+,COGS+,SGA0)	Construction Materials (C+*,COGS+*,SGA+*) Leisure Products (C−,COGS−,SGA0) Personal Products (C+,COGS+*,SGA0) Health Care Equip. (C−,COGS0,SGA0) Multi-Utilities (C+,COGS+,SGA0)	Construction & Eng. (C−,COGS−,SGA0) Leisure Products (C+,COGS0,SGA0) Capital Markets (C−,COGS−,SGA-) Gas Utilities (C−*,COGS−*,SGA0) Electric Utilities (C0,COGS0,SGA0)	Metals & Mining (C0,COGS0,SGA0) Machinery (C−,COGS−,SGA−*) Airlines (C+,COGS+,SGA0) Capital Markets (C+,COGS+,SGA0)

that construction materials, construction and engineering, metals and mining, utilities (electric, gas, and multi-utilities), transportation (airlines), light manufacturing industries (e.g. leisure products, life science tools, and health care equipment) are significantly affected by extreme temperatures through the cost channel rather than through revenues (see Table 3).

Over and above our originally hypothesized agricultural and labor productivity channels, the bulk of our empirical evidence is consistent with consumer demand shifts that are driven by extreme temperature events. In particular, Starr-McCluer (2000) builds a model where weather can affect non-market productivity. As a result, extreme weather can affect sales through weather-induced consumer demand shifts across sectors. For instance, extreme weather can make shopping a more or less difficult experience; cold temperatures and precipitation can hinder travel and keep people away from stores and restaurants; hot summer weather may drive consumers toward indoor activities. Similarly, the early onset of seasons such as abnormally cold weather in autumn or the arrival of summer temperatures in spring can shift consumer demand patterns. Starr-McCluer provides empirical evidence consistent with these ideas using sector-level output data. Furthermore, Colacito et al. (2019) use macroeconomic output data to demonstrate that extremely hot temperatures in summer and fall months affect U.S. GDP growth rates.

Our results provide strong support for the consumer demand shift channel. As discussed earlier, about three quarters of the significant temperature-earnings relations we document are driven by revenue effects. Many of these affected industries are in the consumer sector (e.g., leisure products; textile, apparel, and luxury goods; hotels and restaurants; beverages; personal products; specialty retail; and airlines). In the context of a consumer demand channel, the broad pattern of extreme weather effects among these industries seems sensible. For example, a cold shock in spring (Q2) reduces demand for clothing, traveling, eating out, beverage purchases, and personal products (e.g. summer cosmetics), consistent with a reduction of revenues and profitability among firms in the textile, apparel, and luxury goods, hotels and restaurants, beverages, and personal products industries.

3.2. Economic mechanism tests and robustness checks

We conduct a series of tests aimed at better understanding the mechanisms highlighted in our analysis to this point. We also present the results of several robustness checks.[18]

3.2.1. Consumer demand shifts

In our first set of tests, we utilize SafeGraph data to directly test the weather-induced consumer demand shift channel. Specifically, we match SafeGraph establishments to daily PRISM weather data based on the SafeGraph-provided latitude-longitude coordinates. We then test whether there is evidence of decreased foot traffic to these establishments on days when temperatures surpass industry-specific critical temperature thresholds. Given the

[18] We thank an anonymous referee for suggesting these valuable tests.

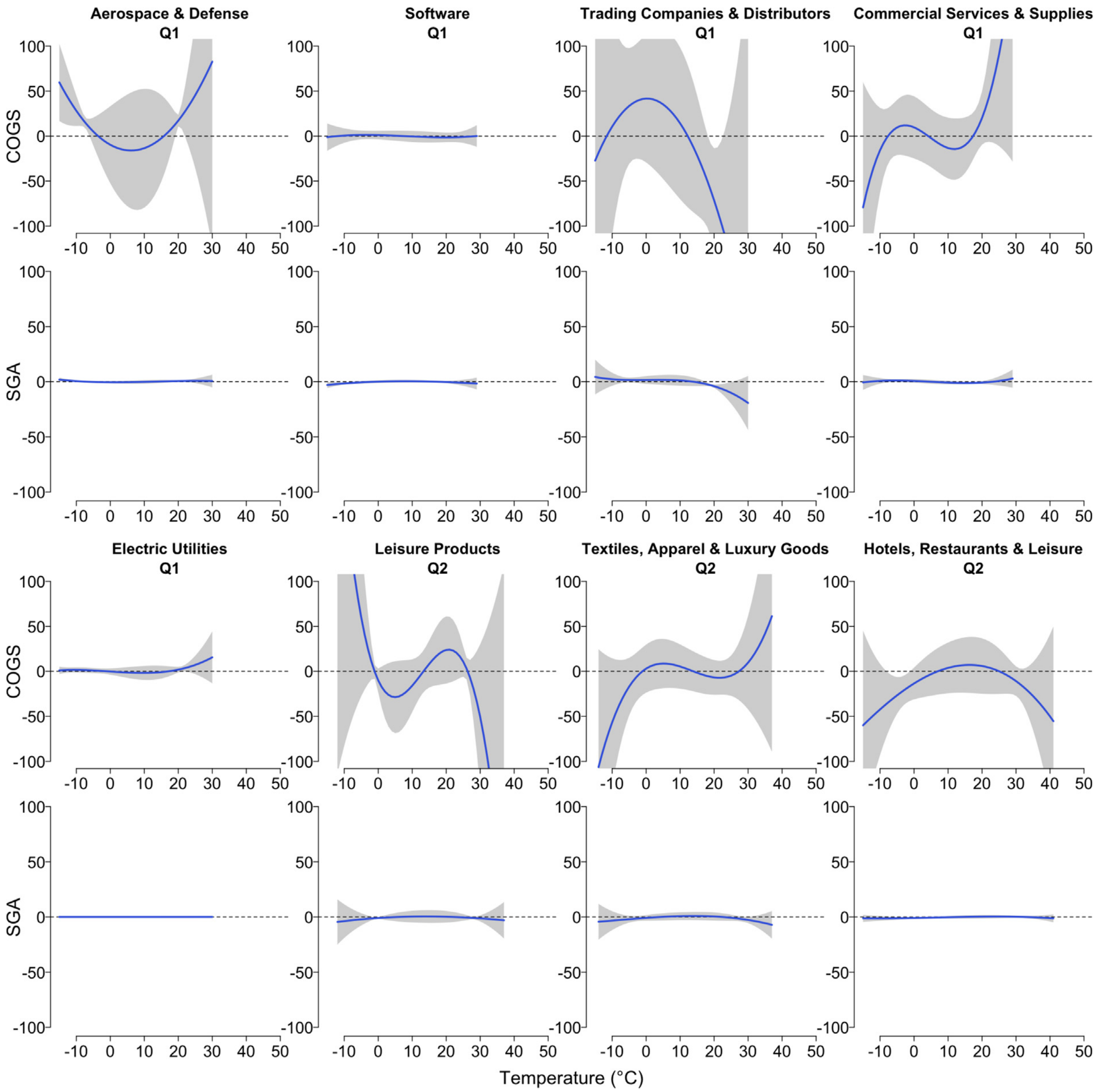

Fig. 7. Nonlinear Relations Between Firm Cost of Goods Sold, SG&A, and Temperature. The figure displays the nonlinear effects of temperature exposure on the cost of goods sold and selling, general, and administrative (SG&A) expense components of operating costs based on regression specifications (Eq. (2)) estimated for fiscal quarters ending during each calendar quarter of the year (Q1-Q4). We plot estimated response functions surrounded by ±2 standard error bands. Standard errors are clustered by firm and quarter. Impacts (y-axis) are reported in log points multiplied by 1,000. Each panel focuses on a specific 6-digit GICS industry and we restrict the analysis to industries where there are significant relations between temperature shocks and profitability (Fig. 5).

extremely large size of the SafeGraph data and our matching of daily temperature exposures, we focus these tests on a set of 870,464 establishments in the Hotels and Restaurants (NAICS 72) and Arts, Entertainment, and Recreation (NAICS 71) industries. We match daily min, max, and mean temperatures, as well as precipitation, from PRISM to each establishment between January 2018 and November 2021.

Our baseline earnings results indicate that firms in the Hotels and Restaurants industry (GICS 253010, which encompasses casinos and gaming, hotels and resorts, leisure facilities, and restaurants) exhibit a negative sensitivity to extremely cold temperature in the months of April, May, and June (i.e., Q2). Hence, we test whether there is evidence that foot traffic to these establishments is abnormally low on days when temperatures fall to the critical temperature threshold of 4°C or below. Because all critical temperature days fall within Q2, we limit our sample to observations in April, May, and June.

We implement the test by regressing the number of daily establishment visits on a temperature shock indica-

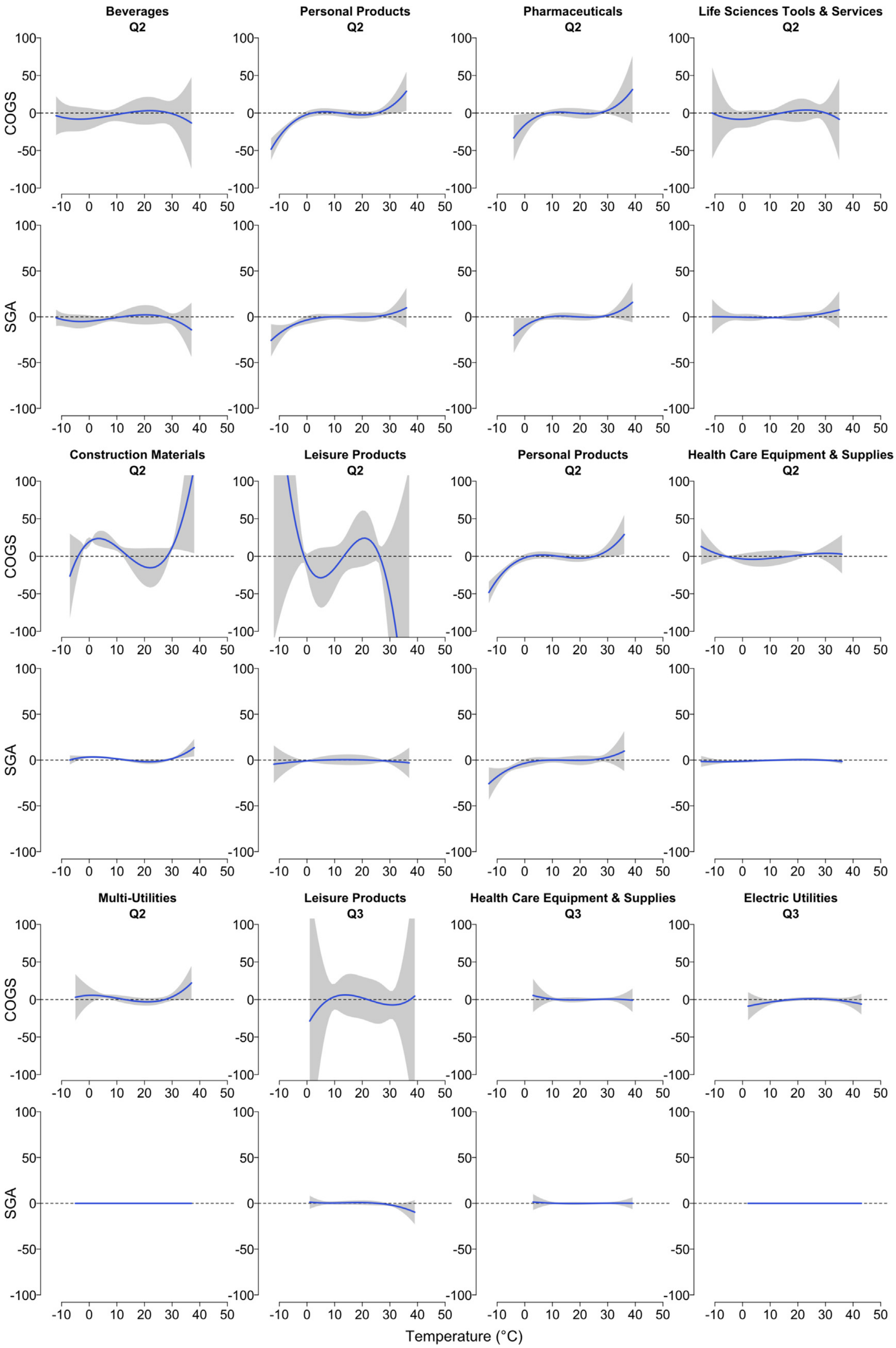

Fig. 7. Continued

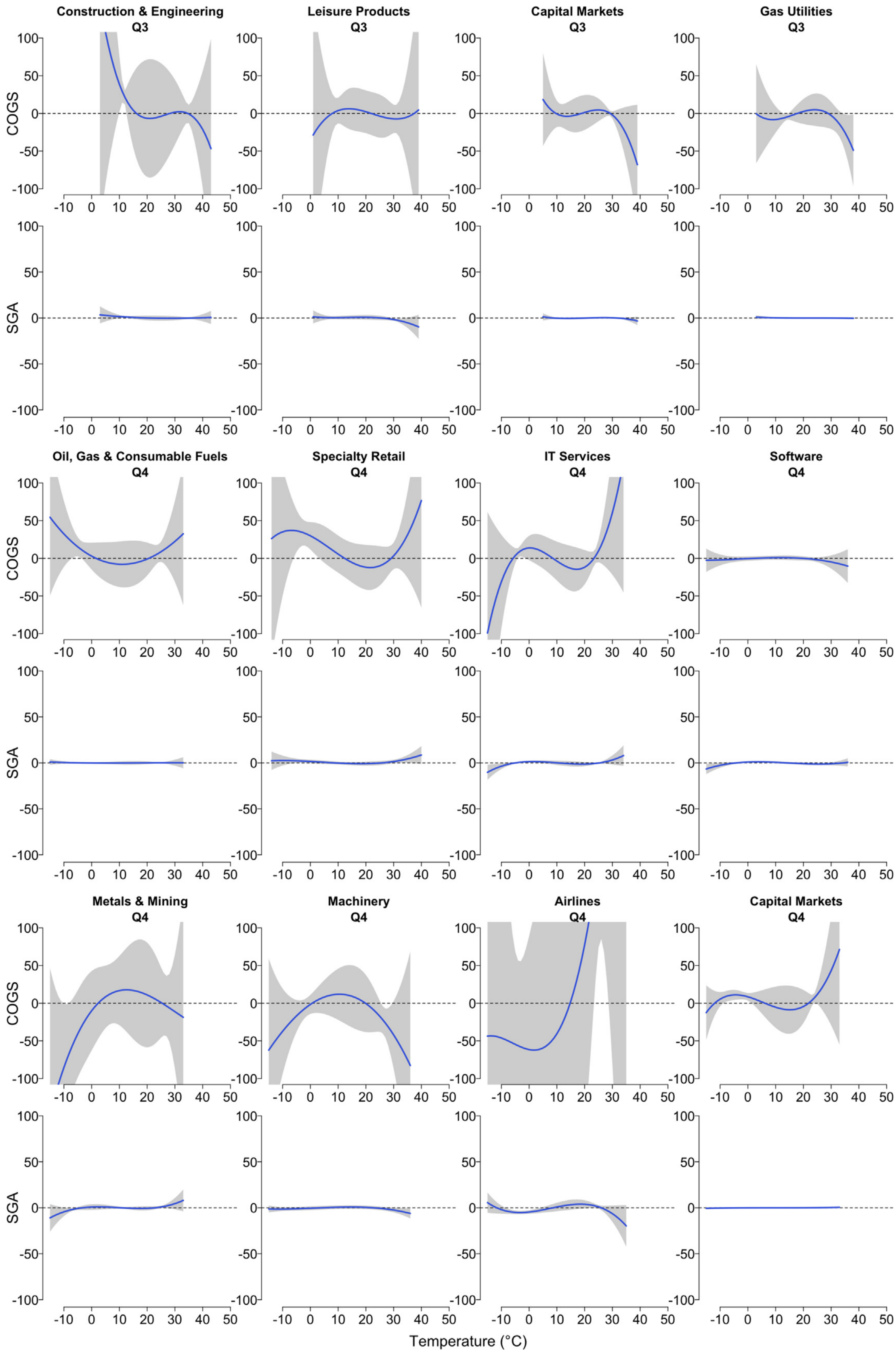

Fig. 7. Continued

Table 5

SafeGraph establishment visits and extreme temperature events. This table reports Poisson fixed effects regressions of daily establishment visits on extreme temperature days. The sample includes SafeGraph establishments with 2-digit NAICS codes of 71–72 with daily visit data in April, May, and June of 2018 to 2021. We define extreme temperature days (temp shock day indicator) as days on which firms are exposed to temperatures below 4°C, the critical threshold for which we find a statistically significant negative effect on Q2 Hotels & Restaurants profitability in Table 2. In Panel B, we interact the temp shock day indicator with a weekend indicator, equal to one on Friday, Saturdays, and Sundays, and zero otherwise. All regressions include quarter-by-establishment fixed effects and place-by-day-of-week fixed effects. In both panels, column 1 includes the full sample of observations. In columns 2 to 6, we focus on subsamples of establishments within 4-digit NAICS classifications. All regressions include controls for mean daily temperature and linear and squared daily precipitation. z-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering at the quarter-by-establishment level.

Panel A: Baseline Poisson regressions

	NAICS 71–72 Full Sample (1)	NAICS 7112 Spectator Sports (2)	NAICS 7121 Museums & Historical Places (3)	NAICS 7132 Gambling Establishments (4)	NAICS 7224 Drinking Places (Beverages) (5)	NAICS 7225 Restaurants (6)
Temp shock day	−0.0508	−0.0598	−0.0893	−0.0250	−0.0540	−0.0349
	(−33.26)	(−3.64)	(−16.95)	(−1.96)	(−11.17)	(−38.14)
Mean temp (°C)	0.0077	−0.0015	0.0101	0.0097	0.0063	0.0071
	(65.41)	(−1.42)	(22.84)	(8.84)	(25.00)	(117.62)
Precipitation (mm)	−0.0011	−0.0018	−0.0042	0.0015	−0.0001	−0.0001
	(−31.07)	(−3.08)	(−28.22)	(2.51)	(−1.22)	(−7.10)
Pseudo R^2	0.751	0.719	0.815	0.891	0.674	0.698
N	233,172,203	1,147,105	37,459,200	683,536	14,960,184	178,922,178
Squared precip. control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr × Place FE	Yes	Yes	Yes	Yes	Yes	Yes
Place × Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Poisson regressions with weekend interactions

	NAICS 71–72 Full Sample (1)	NAICS 7112 Spectator Sports (2)	NAICS 7121 Museums & Historical Places (3)	NAICS 7132 Gambling Establishments (4)	NAICS 7224 Drinking Places (Beverages) (5)	NAICS 7225 Restaurants (6)
Temp shock day	−0.0356	−0.0211	−0.0648	−0.0150	−0.0476	−0.0227
	(−21.66)	(−1.22)	(−11.79)	(−1.23)	(−7.78)	(−21.80)
Temp shock day × Weekend	−0.0373	−0.0919	−0.0616	−0.0212	−0.0145	−0.0297
	(−29.93)	(−3.64)	(−15.48)	(−2.48)	(−3.33)	(−36.07)
Pseudo R^2	0.751	0.719	0.815	0.891	0.674	0.698
N	233,172,203	1,147,105	37,459,200	683,536	14,960,184	178,922,178
Mean temp. control	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr × Place FE	Yes	Yes	Yes	Yes	Yes	Yes
Place × Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes

tor that is equal to 1 if the temperature falls to 4°C or below that day, and zero otherwise. We also include mean temperature as well as linear and squared daily precipitation as control variables. Further, we include quarter-by-establishment fixed effects to account for variation in average foot traffic over different years in the sample. We also include place-by-day-of-week fixed effects to account for systematic variation in establishment visits over the course of the week (e.g., weekdays vs. weekends). Following the prescriptions of Cohn et al. (2022), we estimate these regressions using a Poisson fixed effects model with standard errors clustered at the quarter-by-establishment level (Note that we find qualitatively similar results when we follow the common practice of regressing the natural log of one plus the number of visits on the temperature shock indicator and controls. See Appendix Table A.4.).

Our results in Panel A of Table 5 indicate a strong and robust negative effect of temperature shock days on establishment visits. Specifically, we find that in the full sample of establishments in column 1, daily visits drop by over 5% on days when temperatures fall below the critical temperature threshold of 4°C. Importantly, this effect is estimated after controlling for daily mean temperature and precipitation. The estimate is statistically significant at better than the 0.1%-level, with a z-statistic of −3.64. In columns 2 to 6, we split the full sample by 4-digit NAICS codes and separately estimate the effect of extreme temperatures on establishment visits for in the following sub-industries: spectator sports, museums and historical places, gambling establishments, beverage drinking places, and restaurants. Across all these subsamples, we continue to find a strong negative effect on daily visits associated with abnormally cold temperature. Economically, we find that sub-4°C days are associated with decreased daily visits ranging between 2.5 and 8.9%, with z-statistics ranging from −1.96 to 38.14 (p-values from 0.05 to <0.001).

In panel B, we examine whether the negative effect of extreme temperature days on daily establishment visits is amplified on weekends. We further include an interaction between the temperature shock day indicator and a weekend indicator (the level effect of the weekend indicator is subsumed by the place-by-day-of-week fixed effects). The weekend indicator is set equal to 1 on Saturdays and Sundays. Additionally, because Friday weather may be important for consumers visiting the establishments we examine, we set the weekend indicator equal to 1 on Fridays as well (Note that we find similar results without assigning Fridays as a weekend day. See Appendix Table A.5 for details.). Across all specifications (i.e., for the full sample and for individual sub-industries), we find that the negative effect of sub-4°C days is amplified when extreme temperatures fall on weekends. The interaction effects are economically and statistically significant, with z-statistics ranging from −2.48 to −36.07. Among establishments in the museums and historical places, beverage drinking places, and restaurants sub-industries, as well as for the full sample, we continue to find a strong effect associated with extreme temperatures even on weekdays. In contrast, we find that weekend temperature extremes dominate and drive out the effect of weekday extremes for spectators sports and gambling establishments.

3.2.2. Weekday temperature shocks

In our next set of tests, we further examine the effect of weekdays in order to differentiate between the labor productivity and consumer demand channels. Specifically, we estimate the effect of extreme temperature exposures using only weekday exposures. In contrast to our SafeGraph results, which highlight the importance of weekend extreme temperatures for the consumer demand channel, we expect that focusing on weekday temperature exposures will generate more (less) pronounced results among industries where labor productivity is (is not) likely to be the dominant channel.

In Appendix Table A.6, we find evidence consistent with our conjecture. While many of the industries from our baseline results continue to exhibit sensitivity to extreme temperature, we find that some industries that appear only when focusing on weekday temperatures and others that are absent. For example, the paper & forest products, machinery, and technology hardware industries all exhibit novel earnings sensitivities in Appendix Table A.6 that are not apparent when using both weekday and weekend exposures in our main tests. Importantly, these industries are labor intensive and sensitivities are likely to be driven by a labor productivity channel rather by consumer demand. In contrast, a notable absence when estimating sensitivities using only weekday temperature exposures is the hotels & restaurants industry, consistent with the importance of weekend temperatures for this industry documented in our SafeGraph analysis above. Similarly, the positive sensitivity of airlines to late autumn extreme heat is muted when focusing on weekday temperatures.

3.2.3. Tradable vs. non-tradable industries

Next, we implement a test examining the extent to which the relationship between profitability and extreme temperatures differs across tradable vs. non-tradable sectors of the economy. While firms in non-tradable sectors rely heavily on local demand, firms in non-tradable sectors are less exposed to local demand shocks. Thus, examining the degree to which extreme temperature sensitivities differ across tradable vs. non-tradable sectors allows to better understand the relative importance of the consumer demand vs. complementary channels.

Following the Mian and Sufi (2014) classifications of 4-digit NAICS industries into tradable and non-tradable categories, we classify 6-digit GICS industries into tradable, non-tradable, and other categories as summarized in Appendix Table C.7. We jointly estimate the industry-by-industry extreme temperature earnings sensitivity functions for each calendar quarter and test whether the magnitude of the extreme temperature sensitivities differs across tradable vs. non-tradable industries. Formally, we calculate the economic impact of doubling the exposure to each 5% tail of an industry's temperature distribution. Then, for each tail we implement a Wald-type test of whether the impact magnitudes for tradable industries differ from those of non-tradable industries.

The results of these tests are presented in Table 6. We find that non-tradable industries exhibit greater economic sensitivity to both extreme heat and cold across all quarters. Interestingly, these differences are statistically significant in the spring (Q2) and autumn (Q4) for extremes of the distribution. Thus, whereas we find no evidence that tradables are more sensitive than non-tradables, we do find statistical evidence consistent with the local consumer demand channel in spring and autumn.

3.2.4. Adaptation over time

In addition to documenting the sensitivity of earnings to extreme temperatures, it is important to understand the degree to which firms exhibit adaptation to extreme temperatures over time. To that end, we conduct a sub-period test. We jointly estimate the industry-by-industry extreme temperature earnings sensitivity functions for each calendar quarter in the first and second halves of the sample (i.e., 1990–2002 vs. 2003–2015). We then test whether the magnitude of the extreme temperature sensitivities decreases over time. Formally, we take the difference between the economic impact of doubling the exposure to each 5% tail of an industry's temperature distribution in the first vs. second half of the sample, and test whether the differences are jointly equal to zero.

The results of these tests are presented in Table 6. We find that firm profits are less sensitive to temperature shocks across all seasons in the latter half of the sample for both temperature extremes. Wald test statistics indicate statistically significant decreases in industry temperature-earnings sensitivities. In most cases (6 out of 8), these differences are significant at better than the 1% level, with highly significant p-values of 0.015 and 0.038 in the remaining cases. Overall, our tests provide strong evidence of what appears to be adaptation to extreme temperatures over the course of our sample.

3.2.5. Heat-sensitive sectors

We augment our analysis in section 3.1.2 by testing the extent to which the relationship between profitability and extreme temperatures differs across heat-sensitive and non-heat-sensitive sectors. Following the classifications of Graff-Zivin and Neidell (2014), we classify 6-digit GICS industries into heat-sensitive and non-heat-sensitive categories as summarized in C.7. We jointly estimate the industry-by-industry extreme temperature earnings sensitivity functions for each calendar quarter and test whether

Table 6

Tests of Differences in Earnings Impacts. This table reports statistics for tests of differences in economic impacts associated with doubling of the extreme 5% tails of the temperature distribution industry firms experience during each calendar quarter of the year. The row labeled Tradables vs. Non-Tradables examines whether the magnitude of extreme temperature impacts differs between tradable and non-tradable industries. Tradable and non-tradable industries are classified following Mian and Sufi (2014) and according to Appendix Table A.7. The row labeled First vs. Second Half examines whether the magnitude of extreme temperature impacts for a given industry differ from the first to second half of the sample. The row labeled Heat Sensitive vs. Non-Sensitive examines whether the magnitude of extreme temperature impacts differs between heat-sensitive and non-heat-sensitive industries. Heat-sensitive and non-sensitive industries are classified following Graff-Zivin and Neidell (2014) and according to Appendix Table A.7. *p*-values reported in square brackets below Wald test statistics are calculated using standard errors clustered by firm and quarter.

	Difference: Left 5% Tail ×2				Difference: Right 5% Tail ×2			
Test	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Tradables vs. Non-Tradables	1.121	36.929	0.028	57.424	0.007	8.064	0.623	32.773
	[0.290]	[<0.001]	[>0.999]	[<0.001]	[0.931]	[0.005]	[0.430]	[<0.001]
First vs. Second Half	84.915	94.495	135.644	2762.749	105.136	79.618	122.641	463.096
	[0.015]	[0.002]	[<0.001]	[<0.001]	[<0.001]	[0.038]	[<0.001]	[<0.001]
Heat Sensitive vs. Non-Sensitive	3.371	36.689	0.914	35.914	2.849	33.358	7.128	9.645
	[0.066]	[<0.001]	[0.339]	[<0.001]	[0.091]	[<0.001]	[0.008]	[0.002]

the magnitude of the extreme temperature sensitivities differs across heat-sensitive vs. non-heat-sensitive industries. Formally, we calculate the economic impact of doubling the exposure to each 5% tail of an industry's temperature distribution. Then, for each tail we implement a Wald-type test of whether the impact magnitudes for heat-sensitive industries differ from those of non-heat-sensitive industries.

The results of these tests are presented in Table 6. Consistent with our observations in Section 3.1.2 and the prior findings of Graff-Zivin and Neidell, we find that heat-sensitive industries indeed exhibit greater sensitivity to extreme temperatures in almost all cases. For right tail extremes that are the focus of Graff-Zivin and Neidell, we find that the difference between heat-sensitive and non-sensitive industries is statistically significant at better than the 1% level in Q2 through Q4. In Q1, the difference is significant at the 10% level. Furthermore, in the left tail, we find that differences are significant at the 0.1% level in half of quarters (Q2 and Q4), and have a *p*-value of 0.066 in Q1. Overall, our findings align with those of Graff-Zivin and Neidell (2014).

3.2.6. Alternative profitability measures

It is important to note that the EPS measure used in our main tests does not include extraordinary items. To the extent that firms treat gains or losses associated with extreme temperatures as one-time events, they may not be detected by our tests. To examine this possibility and provide transparency and robustness in our analysis, we re-estimate our tests using three alternative measures. First, we compute a quarterly EPS measure that includes extraordinary items. Second, we further compute a quarterly EPS measure that includes both extraordinary and special items. Finally, we compute an operating cash flow measure by adding back depreciation and amortization and deferred taxes to the EPS measure that includes both extraordinary and special items. We present the results from these three cases in Appendix Tables A.8–A.10.

We find that relative to our baseline EPS-based effects, the results are stronger, with more sensitive industries uncovered for the more comprehensive earnings measures. We note that our topline EPS-based results can be interpreted as a lower bound for the effects of extreme temperatures, and that the results with measures including extraordinary and special items suggest there is additional sensitivity that researchers and market participants can benefit from attending to.

3.2.7. Placebo test

As a final robustness check, we re-estimate our baseline earnings specifications using future temperature exposures. In Fig. 8, we plot the fraction of industry-calendar quarters featuring extreme temperatures effects that are statistically significant at the 5% level. We find that the proportion of industry-quarter combinations with significant effects drops off significantly when we use future temperature realizations. Whereas we find that about 7% of industry-quarter combinations exhibit significant extreme temperature effects in our baseline tests, this proportion drops below 5% and randomly oscillates between 2.1 and 2.9% when using future temperatures. This finding suggests that the baseline industry-level extreme temperature sensitivities we document are 2 to 3 times more prevalent than one would expect via random chance, and are thus unlikely to be spurious.

Given our body of evidence indicating that extreme temperatures can help to explain earnings and predict earnings announcements in at least some industries, a natural follow-up question is whether financial market participants efficiently account for these effects. To understand the answer to this question, we shift our focus to two outcomes: sell-side analysts' earnings forecasts and stock prices.

3.3. Do analysts understand the impact of extreme temperature?

In this section, we conduct a set of tests aimed at understanding whether analysts account for the effects of extreme temperatures in their forecasts. Further, we aim to explore whether there are analyst characteristics, such as location and political affiliation, that explain the heterogeneity in analysts' reactions to extreme temperature events.

To begin, we examine whether analysts generally account for the effects associated with extreme temperatures. To do so, we estimate specifications similar to that in

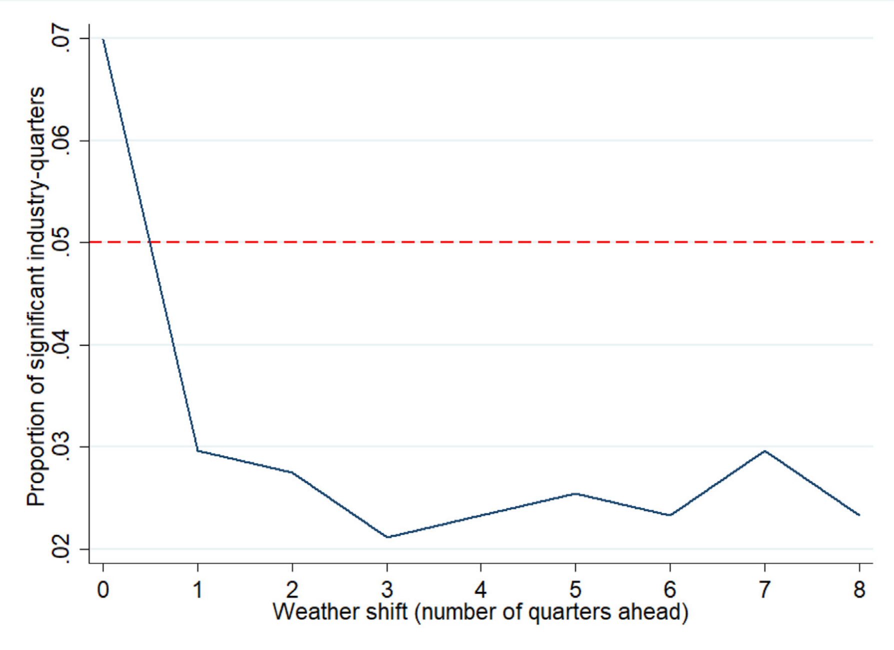

Fig. 8. Placebo Test. The figure plots the proportion of industry-quarter combinations exhibiting extreme temperature effects that are statistically significant at the 5% level when estimated using h-quarter ahead weather realizations. h ranges from 0 to 8. The baseline results in the paper correspond to $h = 0$, where weather in contemporaneous with the fiscal quarter. For h ranging from 1 to 8, weather corresponds to future fiscal quarters. A horizontal dashed line corresponding to 5% is plotted for reference.

Eq. (2), but replace firm profitability with analyst consensus forecasts as of firms' earnings announcement dates. If the observed relationships between earnings and weather variables are mirrored in analyst consensus forecasts, then this would be evidence that analysts understand the importance of extreme temperature exposure. In contrast, for industries and calendar quarters where an important earnings effect exists, a flat relation between the consensus forecast and temperature exposure would indicate that analysts do not generally account for extreme temperatures.

Another way to assess whether analysts fully or only partially aggregate the effects of temperature exposure is to examine earnings forecast surprises. Specifically, we estimate specifications similar to Eq. (2), but with standardized unexpected earnings (SUE) relative to analysts' forecasts as the dependent variable (e.g. Livnat and Mendenhall, 2006). SUE is defined as actual earnings minus the mean of analysts' forecasts as of the end of the fiscal quarter, scaled by end-of-quarter share price.

Fig. 9 shows the analyst consensus forecast estimates for the 24 industries (32 industry-quarters) in our sample where temperature extremes affect earnings. Table 7 shows the reported earnings (E), analyst consensus forecast estimates (F), and earnings surprise (S) results for the industries that have significant earnings shocks triggered by extreme temperature events in Table 2. For most industries, analysts anticipate at least part of the earnings shocks by the time earnings are announced. However, the consensus forecasts miss or do not fully account for the effects of temperature extremes in seven industries (leisure products; personal products; life science tools; construction and engineering; trading companies and distributors; commercial services and supplies; and machinery), resulting in statistically significant earnings surprises. Importantly, there are no industries where analysts adjust their forecasts in the opposite direction to the actual effects associated with temperature shocks.

Analysts anticipate earnings shocks in many, but not all, of the industries by quarter-end. As reported earlier, earnings for electric utilities are hurt by extremely warm winter and cool summer temperatures. Analysts anticipate such trends, resulting in no earnings surprise. Similarly, summer heat waves are bad news for corporate profitability among firms in four industries. Analysts anticipate the earnings shocks for three of the industries (leisure products; gas utilities; and capital markets), but miss the earnings shocks for construction and engineering, resulting in significant earnings surprises.

Extreme heat in autumn months is good news for three industries (metals and mining; airlines; and capital markets). Analysts generally anticipate this good news, resulting in no significant earnings surprise in these three industries. However, analysts seem to miss the fact that extreme autumn heat is also generally bad news for firms in the machinery industry. As a result, warm autumn temperatures are associated with significantly negative earnings surprises.

Table 7 further shows that analysts generally anticipate that cold spring temperatures are bad news for earnings in five industries, resulting in no significant earnings surprises. In contrast, analysts do not fully incorporate the fact that cold spring temperatures can also be good news. In particular, we find that cold spring temperature shocks are associated with significantly positive earnings surprises in

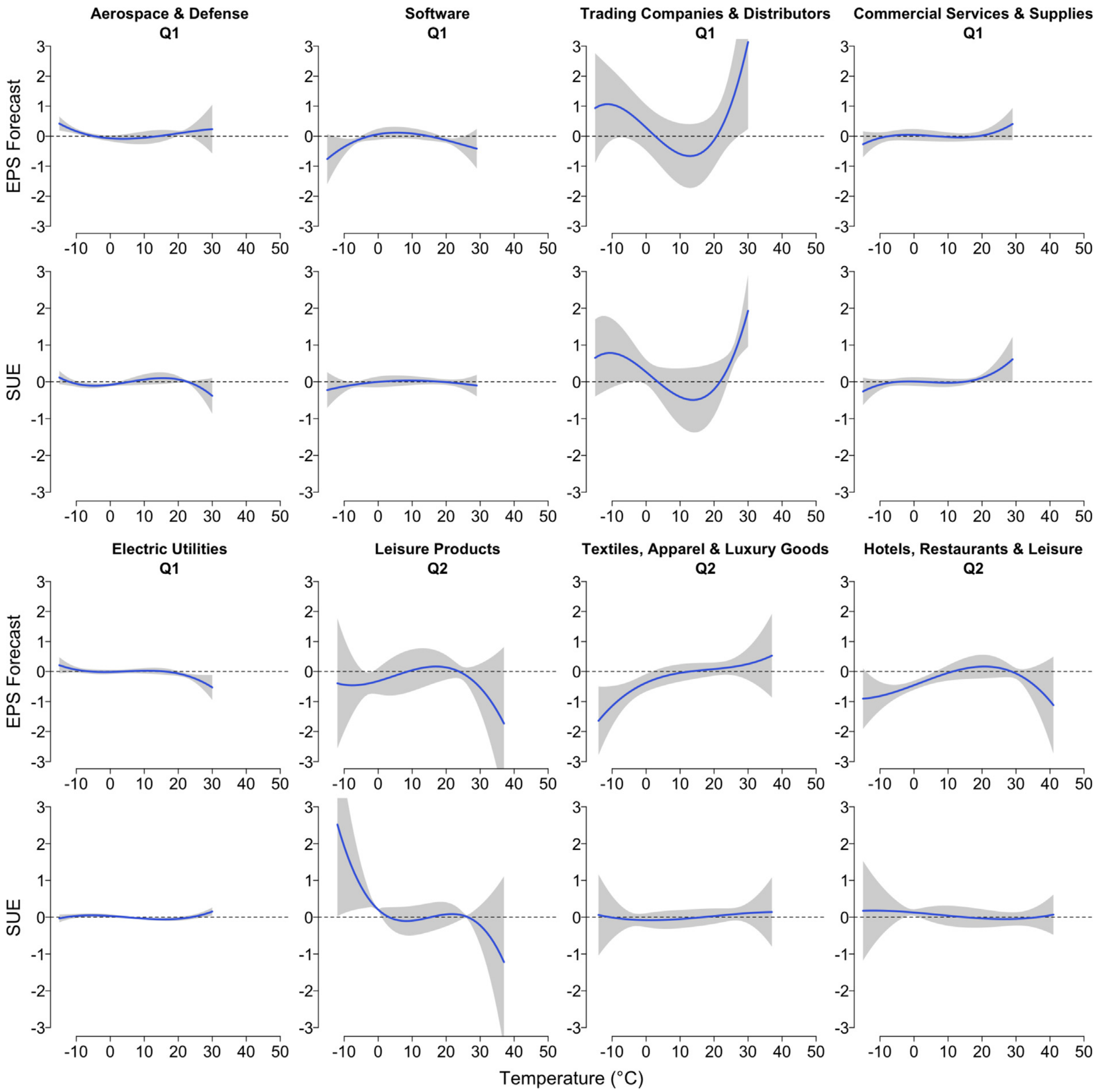

Fig. 9. Nonlinear Relations Between Firm Mean Earnings Forecasts, Earnings Surprises, and Temperature. The figure displays the nonlinear effects of temperature exposure on analysts' mean consensus earnings forecasts and earnings surprises (SUE) based on regression specifications (Eq. (2)) estimated for fiscal quarters ending during each calendar quarter of the year (Q1-Q4). We plot estimated response functions surrounded by ±2 standard error bands. Standard errors are clustered by firm and quarter. Impacts (y-axis) are reported in log points multiplied by 1,000. Each panel focuses on a specific 6-digit GICS industry and we restrict the analysis to industries where there are significant relations between temperature shocks and profitability (Fig. 5).

the two industries with positive earnings shocks (leisure products and life science tools).

3.4. Extreme temperature reactions among analysts and investors

Next, we investigate how quickly analysts and investors respond to intra-quarter extreme temperature events for industries where we find that exposure to such events matters. We also aim to understand how geographic variation in climate change beliefs affects the responsiveness of analysts' earnings estimates and stock prices to extreme temperature.

To estimate analysts' and investors' responsiveness to extreme temperature events, we conduct separate event studies. Specifically, we define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations

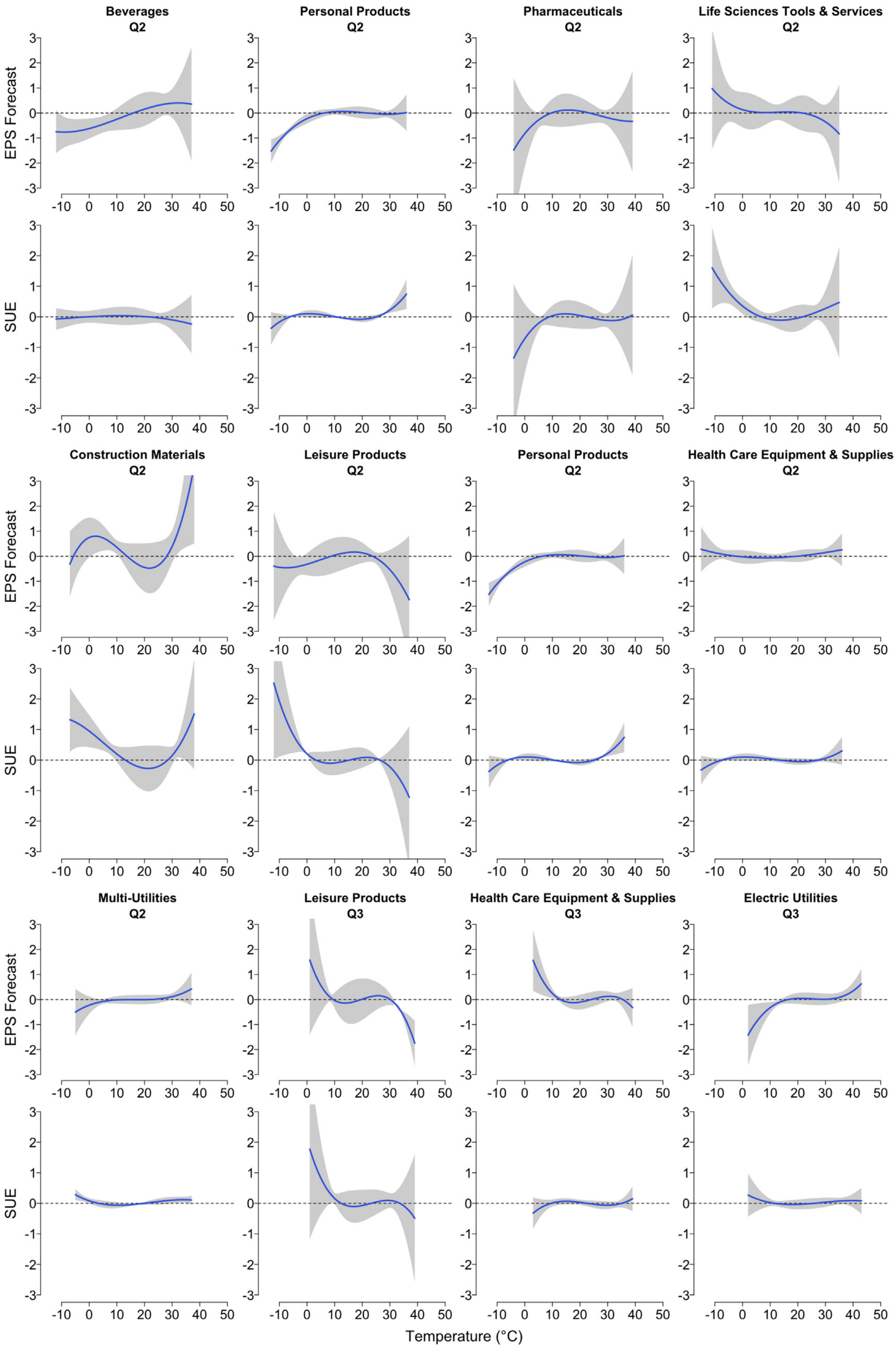

Fig. 9. Continued

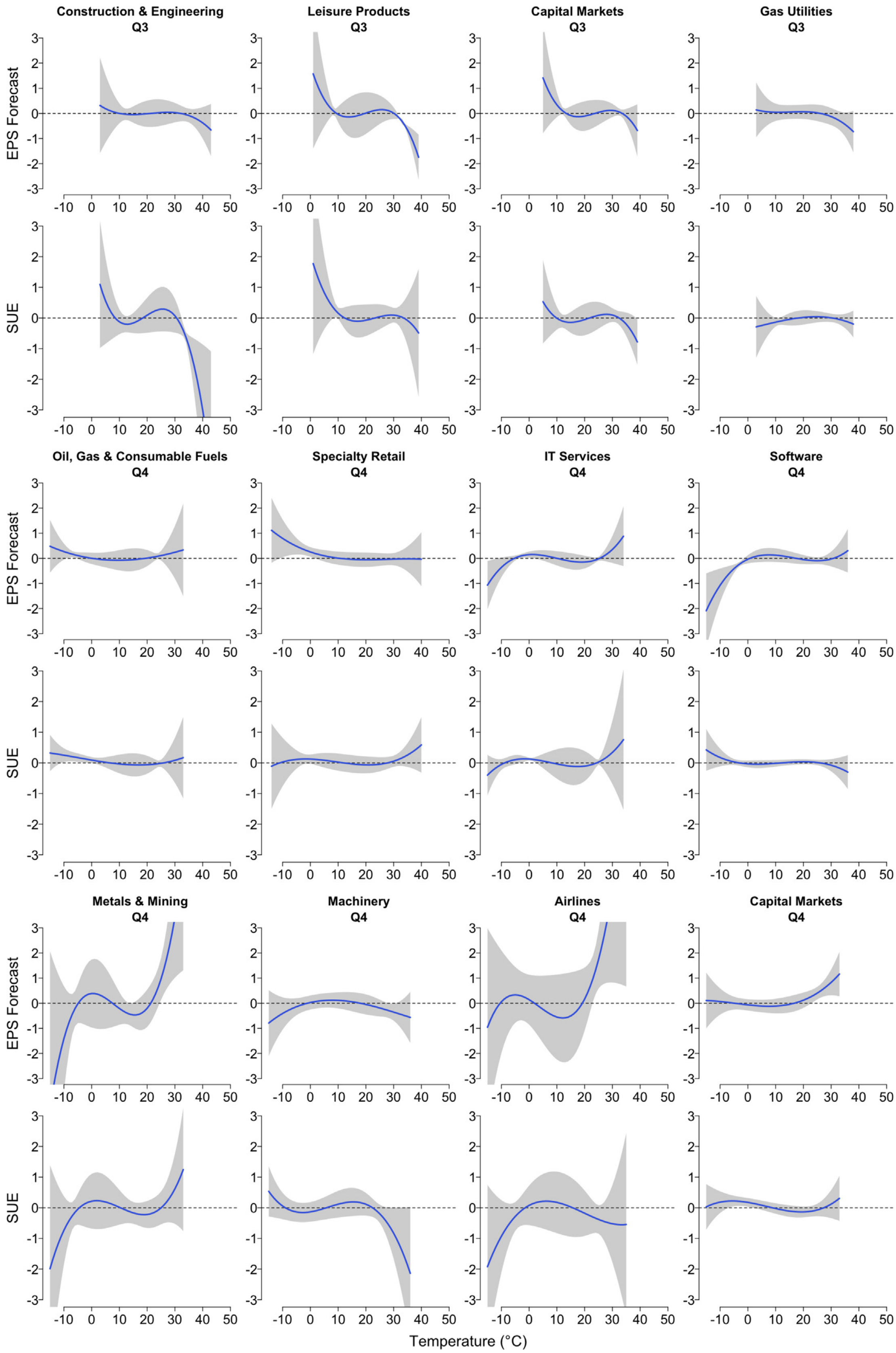

Fig. 9. Continued

Table 7

Quarterly Sensitivity of Mean Earnings Forecasts and Earnings Surprises to Extreme Cold and Heat. This table reports directional effects for earnings per share, analysts' mean earnings forecasts, and earnings surprises among GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), with earnings forecasts and earnings surprises as the dependent variables and associated response functions displayed in Fig. 9. We focus on industries with a statistically significant relation between EPS and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) a given measure, while 0 indicates that extreme temperature exposure has approximately no effect. Earnings, forecast earnings, and earnings surprises are respectively denoted by E, F, and S. For forecast earnings and earnings surprises, * indicates that the effect of extreme temperature exposure is statistically significant at the 5% level.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (E+,F+*,S0) Software (E−,F−*,S0)	Leisure Products (E+,F0,S+*) Textile, Apparel & Lux. (E−,F−*,S0) Hotels & Restuarants (E−,F−*,S0) Beverages (E−,F−*,S0) Personal Products (E−,F−*,S0) Pharmaceuticals (E−,F−,S−) Life Science Tools (E+,F+,S+*)	Leisure Products (E+,F+,S+) Health Care Equip. (E+,F+*,S0) Electric Utilities (E−,F−*,S0)	Oil, Gas & Fuels (E+,F0,S+) Speciality Retail (E+,F+*,S0) IT Services (E−,F−*,S0) Software (E−,F−*,S0)
Heat Shock Sensitivity	Trading Cos. & Distributors (E+,F+*,S+*) Commercial Serv. & Supplies (E+,F+,S+*) Electric Utilities (E−,F−*,S0)	Construction Materials (E+,F+*,S+) Leisure Products (E−,F−,S−) Personal Products (E+,F0,S+*) Health Care Equip. (E+,F0,S+) Multi-Utilities (E+,F+,S0)	Construction & Eng. (E−,F0,S−*) Leisure Products (E−,F−*,S0) Capital Markets (E−,F−,S−) Gas Utilities (E−,F−,S0) Electric Utilities (E+,F+*,S0)	Metals & Mining (E+,F+*,S+) Machinery (E−,F−,S−*) Airlines (E+,F+*,S0) Capital Markets (E+,F+*,S0)

Table 8

Analyst forecasts and stock prices surrounding extreme temperature events. This table reports estimates of changes in analysts' consensus quarterly EPS forecasts (scaled by beginning-of-quarter share price) and stock prices surrounding extreme temperature events over several event windows. We define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. In column 1, we compare the average consensus forecasts in the pre- vs. post-event windows. We multiply forecasts for temperature events associated with a positive effect on earnings by negative one and then demean forecasts within each event window. In column 2, we calculate and report cumulative abnormal returns (CARs) over each event window. For each extreme temperature event, we collect data on daily stock returns in the [−50,+20] day event time window relative to the temperature event date. We then estimate factor regressions using the Carhart (1997) 4-factor model for each firm-event over the 30 days from day −50 to day −21. Using the estimated factor coefficients, we calculate normal and abnormal returns over the period [−20,+20]. We multiply abnormal returns by negative one for temperature events associated with a positive effect on earnings. *t*-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering across events within the same fiscal quarter.

Event window (days)	Mean consensus forecast (1)	Cumulative abnormal return (2)
[−20,+20]	0.003	0.003
	(0.10)	(0.64)
[−10,+10]	0.007	0.001
	(0.30)	(0.43)
[−5,+5]	0.005	0.001
	(0.23)	(0.44)
[−1,+1]	0.007	0.001
	(0.37)	(0.95)
N events	8,584	8,584

rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. Importantly, event dates vary significantly, even within the same industry, due to the combination of weather's location-specificity and variation in firms' geographic footprints. We then measure and compare how the consensus forecast and stock prices respectively change over a post-event window among firms that are subject to intra-quarter temperature shocks.

The results of our earnings forecast event study tests are tabulated in column 1 of Table 8. We present estimates of changes in analysts' consensus quarterly EPS forecasts surrounding extreme temperature events over several event windows. For each event window, we compare the

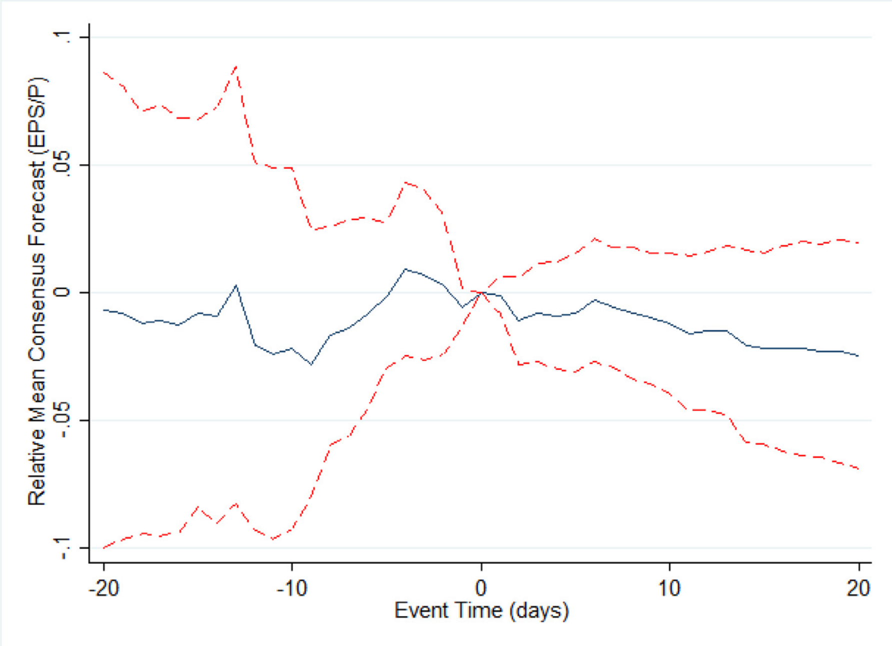

Fig. 10. Mean Consensus Forecasts, Relative to Event Date. The figure plots the evolution of mean consensus forecasts (scaled by beginning-of-quarter share price) in event time relative to the consensus forecast on the event date (solid line). Also plotted are ±2 standard error bands (dashed lines). We define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. We multiply forecasts for temperature events associated with a positive effect on earnings by negative one and then demean forecasts within each event window.

average consensus forecasts in the pre- vs. post-event windows. Since temperature events can imply either good or bad news, we multiply forecasts for temperature events associated with a positive effect on earnings by negative one and then demean forecasts within each event window. Thus, to the extent that analysts do respond to temperature events (*Hypothesis 2*), we should find that the average consensus forecast decreases.

Across 8,584 extreme temperature events, we find no evidence that analysts adjust their EPS forecasts after the firms they cover have experienced an extreme temperature event. Specifically, across the four event windows under consideration ([−20,+20], [−10,+10], [−5,+5], and [−1,+1]), we find that the post- vs. pre-event mean consensus forecast difference is economically small and statistically insignificant (t-statistics between 0.10 and 0.37). Figure 10 plots the evolution of mean consensus forecasts in event time relative to the consensus forecast on the event date. Also plotted are ±2 standard error bands. Consistent with the regression evidence in Table 8, column 1, we see that the mean consensus forecast does not significantly differ from that on the event date in the pre- and post-event windows.[19]

The estimates from our stock price adjustment tests are presented in column 2 of Table 8. For each of the extreme temperature events, we collect data on daily stock returns in the [−50,+20] day event time window relative to the temperature event date. We then estimate factor regressions using the Carhart (1997) 4-factor model for each firm-event over the 30 days from day −50 to day −21. Using the estimated factor coefficients, we calculate normal and abnormal returns over the period [−20,+20]. As before, we multiply abnormal returns by negative one for temperature events associated with a positive effect on earnings so that, to the extent investors do react to temperature shocks, we should find they do so in a negative way. We then calculate cumulative abnormal returns (CARs) over the same event windows considered in our examination of analysts (i.e., [−20,+20], [−10,+10], [−5,+5], and [−1,+1]).

We find that CARs over each of the event windows are economically small and statistically insignificant. For example, over the [−20,+20] day event window, we find that CARs are positive, not negative, amounting to 0.3% (t-statistic = 0.64). The lack of a reaction to temperature events can be seen in Fig. 11, where we plot CARs from day −20 to each specified day, up to day +20. We find a relatively flat relationship between days in the event window and CARs, with all 95% confidence intervals spanning the zero return threshold.

Taken together, our event study results suggest that analysts and investors are generally unresponsive to extreme temperature events. However, in light of our earlier results (i.e. analysts anticipate earnings shocks in many industries by quarter-end), it is likely that analysts learn about

[19] In additional tests, we find that this slow response is independent of analysts' political affiliations, local views on climate change, and past experiences with temperature shocks. See Appendix C

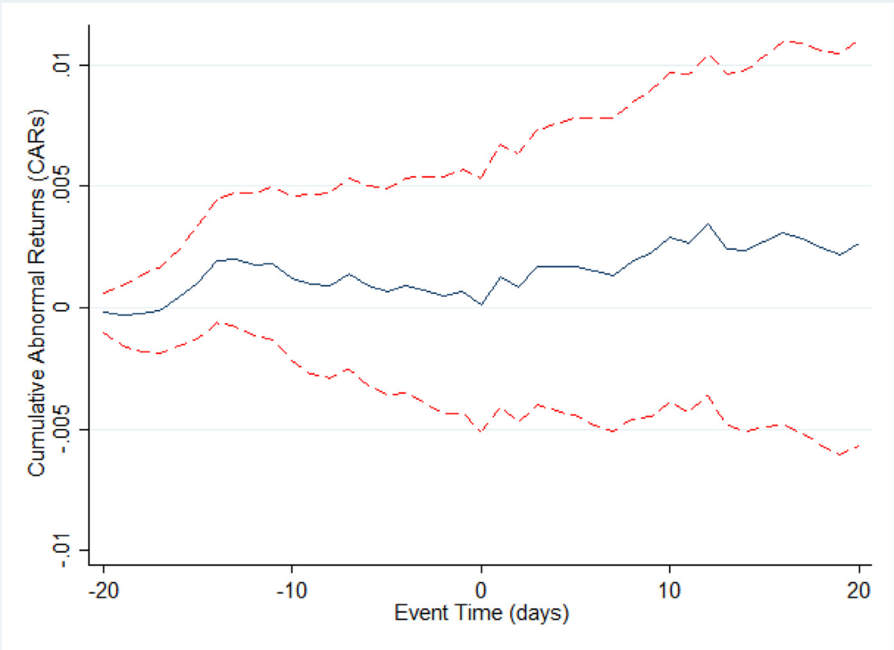

Fig. 11. Cumulative Abnormal Stock Returns, Relative to Event Date. The figure plots cumulative abnormal returns (CARs) from day −20 to each specified day in event time surrounding extreme temperature events. We define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. For each of the extreme temperature events, we collect data on daily stock returns in the [−50,+20] day event time window relative to the temperature event date. We then estimate factor regressions using the Carhart (1997) 4-factor model for each firm-event over the 30 days from day −50 to day −21. Using the estimated factor coefficients, we calculate normal and abnormal returns over the period [−20,+20]. We multiply abnormal returns by negative one for temperature events associated with a positive effect on earnings and cumulate abnormal returns from day −20 to each specified day.

the profitability effects of temperature shocks through indirect channels. For example, analysts may learn about abnormally high or low quarterly earnings through guidance provided by management (e.g. Lev and Penman, 1990; Skinner, 1994; Kasznik and Lev, 1995).

4. Conclusion

In this paper, we study how extreme temperatures affect firm profitability. Motivated by climate scientists' projections of a continuing rise in both average temperatures and the frequency of temperature extremes, we build a panel of quarterly firm-level temperature exposures. We find that the effects of temperature extremes are relatively widespread, affecting earnings in over 40% (24 out of 59) of industries, and are not confined to only agriculture-related firms. We also find that extreme temperature effects are bi-directional, with some industries harmed by temperature shocks while others benefit. We disaggregate the profitability effects of extreme temperatures into separate revenue and operating cost components, and find that revenue effects drive the profitability results in about 75% of cases.

Additionally, we examine analysts' earnings forecasts and earnings surprises relative to these forecasts. We find that in most industries, analysts fully adjust their forecasts to account for temperature shocks by the time earnings are announced. However, in many others (7 out of 24 where earnings are affected), temperature shocks are associated with earnings surprises relative to analyst forecasts. Finally, we find that analysts' earnings forecasts and stock prices do not immediately react to observable intra-quarter temperature shocks, regardless of their political affiliations, local views on climate change, and current and past experiences with extreme temperature events.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Additional robustness tests

There are several important caveats to note with respect to the temperature effects we document. In this appendix section, we present tests accounting for firms' foreign operations, hedging activities, and geography-based adaptation to temperature extremes.

Table A.1

Quarterly Sensitivity of Industry Earnings to Extreme Cold and Heat, Employee Weighted Weather. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), but with weather weighted across firm establishments by number of employees reported in NETS. We focus on industries with a statistically significant relation between earnings and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Construction Materials (−, −9°) Aerospace & Defense (+,−9°) Trading Cos. & Distributors (+,−3°) Software (−, −5°) Gas Utilities (+,−12°)	Oil, Gas & Fuels (+,2°) Building Products (−, 0°) Construction & Eng. (+,0°) Airlines (−, 7°) Textile, Apparel & Lux. (−, 0°) Hotels & Restuarants (−, 6°) Personal Products (−, −4°) Life Science Tools (+,−1°)	Software (−, 7°)	Building Products (+,−4°) Specialty Retail (+,3°) Consumer Finance (+,−11°) IT Services (−, −10°) Software (−, −2°)
Heat Shock Sensitivity	Trading Cos. & Distributors (+,27°) Hotels & Restuarants (+,24°) Personal Products (+,22°)	Construction Materials (+,31°) Personal Products (+,28°) Health Care Equip. (+,29°)	Metals & Mining (+,32°) Construction & Eng. (−, 33°) Capital Markets (−, 34°) Electric Utilities (+,34°)	Metals & Mining (+,26°) Electrical Equipment (+,27°) Machinery (−, 26°) Trading Cos. & Distributors (−, 27°) Airlines (+,23°) Capital Markets (+,29°)

A1. Foreign operations

A first limitation of our temperature exposure measure is that it captures only temperature shocks experienced at firms' operations within the U.S. Since many firms have foreign revenue and cost centers, our measure may only partially capture the effects of temperature on earnings. We address this issue by controlling for firms' foreign earnings exposures using data on their geographic financial segments. Specifically, we include the proportion of firms'

Table A.2

Quarterly Sensitivity of Industry Earnings to Extreme Cold and Heat, Equal Weighted Weather. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), but with weather weighted equally across firm establishments. We focus on industries with a statistically significant relation between earnings and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Construction Materials (−, −8°) Aerospace & Defense (+,−8°) Software (−, −5°)	Textile, Apparel & Lux. (−, −3°) Beverages (−, 5°) Personal Products (−, −7°) Pharmaceuticals (−, 4°) Life Science Tools (+,−5°)	Construction & Eng. (+,12°) Personal Products (+,12°) Health Care Equip. (+,11°) Software (−, 5°) Electric Utilities (−, 12°)	Metals & Mining (−, −10°) Consumer Finance (+,−14°) IT Services (−, −11°) Software (−, −2°)
Heat Shock Sensitivity	Construction Materials (+,27°) Trading Cos. & Distributors (+,22°) Household Durables (−, 21°) Personal Products (+,21°)	Construction Materials (+,30°) Aerospace & Defense (+,32°) Health Care Equip. (+,30°)	Construction & Eng. (−, 33°) Electric Utilities (+,35°)	Metals & Mining (+,29°) Electrical Equipment (+,26°) Machinery (−, 30°)

Table A.3
Earnings Impacts for Doubling 5% Tail Temperature Frequency. This table reports the economic effects associated with a doubling of the extreme 5% tails of the temperature distribution experienced by firms in each 6-digit GICS industry during each calendar quarter of the year. Separate effects for left and right 5% temperature distribution tails are calculated based on estimated earnings response functions and underlying temperature exposure distributions plotted in Internet Appendix Figure IA1. t-statistics reported in parentheses below earnings impact estimates are calculated using standard errors clustered by firm and quarter.

		Left 5% Temp Tail ×2				Right 5% Temp Tail ×2			
Industry	GICS Code	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Energy Equipment & Services	101010	0.0022	0.0004	0.0006	0.0010	0.0023	0.0032	0.0003	0.0014
		(1.45)	(0.64)	(0.87)	(1.19)	(0.57)	(0.94)	(0.14)	(1.10)
Oil, Gas & Consumable Fuels	101020	−0.0013	0.0009	0.0004	0.0032	−0.0011	0.0009	−0.0011	0.0012
		(−1.06)	(1.63)	(1.29)	(3.91)	(−1.02)	(0.75)	(−0.88)	(0.50)
Chemicals	151010	−0.0002	0.0034	0.0036	0.0006	−0.0008	0.0039	0.0009	−0.0021
		(−0.07)	(2.83)	(1.40)	(0.28)	(−0.60)	(1.83)	(0.27)	(−0.64)
Construction Materials	151020	−0.0019	0.0085	0.0024	0.0030	0.0009	0.0095	0.0042	0.0010
		(−0.98)	(3.84)	(0.66)	(1.69)	(0.47)	(4.12)	(0.92)	(0.20)
Containers & Packaging	151030	−0.0052	0.0009	−0.0021	−0.0002	−0.0004	0.0001	−0.0005	0.0002
		(−1.71)	(0.73)	(−1.08)	(−0.14)	(−0.22)	(0.03)	(−0.22)	(0.09)
Metals & Mining	151040	−0.0009	0.0056	−0.0011	−0.0109	0.0088	0.0052	0.0175	0.0084
		(−0.12)	(2.00)	(−0.32)	(−1.36)	(2.01)	(1.63)	(2.89)	(2.15)
Paper & Forest Products	151050	−0.0008	−0.0060	0.0018	−0.0009	0.0041	−0.0039	−0.0025	−0.0002
		(−0.36)	(−1.74)	(1.00)	(−0.29)	(1.95)	(−0.85)	(−0.85)	(−0.02)
Aerospace & Defense	201010	0.0016	0.0015	0.0028	0.0009	0.0005	0.0011	0.0000	0.0036
		(6.98)	(2.15)	(1.43)	(0.33)	(0.68)	(0.75)	(0.01)	(0.88)
Building Products	201020	0.0002	−0.0052	−0.0035	0.0047	0.0010	−0.0034	−0.0051	0.0008
		(0.16)	(−1.21)	(−0.52)	(1.34)	(0.94)	(−0.64)	(−1.02)	(0.16)
Construction & Engineering	201030	0.0013	0.0004	−0.0009	−0.0062	0.0035	−0.0042	−0.0097	−0.0022
		(0.68)	(0.85)	(−0.54)	(−1.39)	(1.17)	(−1.33)	(−3.74)	(−0.83)
Electrical Equipment	201040	0.0001	0.0000	−0.0015	0.0029	−0.0005	−0.0006	−0.0008	0.0015
		(0.08)	(−0.06)	(−2.14)	(0.87)	(−0.42)	(−0.61)	(−0.81)	(2.02)
Machinery	201060	−0.0011	0.0022	−0.0027	−0.0025	0.0004	0.0003	−0.0013	−0.0059
		(−0.91)	(2.06)	(−2.48)	(−0.92)	(0.43)	(0.27)	(−1.56)	(−2.21)
Trading Companies & Distributors	201070	0.0100	0.0012	0.0010	0.0013	0.0103	−0.0008	−0.0003	−0.0211
		(2.06)	(0.81)	(0.88)	(0.27)	(2.19)	(−0.42)	(−0.10)	(−1.84)
Commercial Services & Supplies	202010	−0.0019	−0.0004	−0.0002	−0.0071	0.0018	0.0011	0.0017	−0.0002
		(−1.60)	(−0.66)	(−0.22)	(−1.35)	(2.36)	(1.29)	(1.91)	(−0.08)
Professional Services	202020	0.0005	0.0005	−0.0003	−0.0024	−0.0006	−0.0003	−0.0034	−0.0011
		(0.31)	(0.67)	(−0.21)	(−1.33)	(−0.59)	(−0.12)	(−1.66)	(−0.41)
Air Freight & Logistics	203010	−0.0073	−0.0013	0.0025	−0.0006	0.0027	−0.0008	−0.0014	0.0010
		(−1.45)	(−1.60)	(2.70)	(−0.32)	(1.29)	(−0.29)	(−0.67)	(0.53)
Airlines	203020	0.0037	−0.0192	0.0058	−0.0043	0.0005	−0.0056	0.0130	0.0190
		(0.39)	(−2.99)	(0.66)	(−0.76)	(0.04)	(−1.64)	(1.41)	(2.57)
Road & Rail	203040	0.0024	−0.0016	−0.0011	−0.0001	−0.0005	−0.0021	0.0006	−0.0043
		(0.96)	(−2.34)	(−0.51)	(−0.05)	(−0.31)	(−1.18)	(0.32)	(−1.37)
Auto Components	251010	−0.0065	−0.0015	0.0048	−0.0054	−0.0032	−0.0002	0.0061	0.0059
		(−1.27)	(−1.94)	(0.56)	(−0.61)	(−0.48)	(−0.09)	(0.79)	(0.64)
Household Durables	252010	−0.0005	0.0010	−0.0015	−0.0001	−0.0026	−0.0011	0.0000	0.0099
		(−0.14)	(0.71)	(−1.09)	(−0.04)	(−0.65)	(−0.36)	(0.01)	(1.89)
Leisure Products	252020	0.0023	−0.0002	0.0032	0.0022	−0.0006	−0.0058	−0.0022	−0.0011
		(0.96)	(−0.14)	(3.06)	(0.64)	(−0.57)	(−1.70)	(−1.73)	(−0.26)
Textiles, Apparel & Luxury Goods	252030	0.0008	−0.0035	−0.0038	−0.0022	−0.0012	0.0025	0.0011	0.0008
		(0.93)	(−3.33)	(−2.18)	(−1.04)	(−0.79)	(1.11)	(0.50)	(0.24)
Hotels, Restaurants & Leisure	253010	0.0007	−0.0021	−0.0020	0.0013	0.0007	−0.0018	−0.0029	−0.0024
		(0.83)	(−4.37)	(−1.65)	(1.54)	(1.68)	(−1.31)	(−1.13)	(−1.69)
Diversified Consumer Services	253020	−0.0052	−0.0013	−0.0030	0.0008	−0.0061	−0.0007	−0.0004	0.0000
		(−2.19)	(−0.85)	(−1.04)	(0.70)	(−0.93)	(−0.44)	(−0.20)	(0.02)
Media	254010	0.0027	−0.0044	−0.0043	−0.0065	0.0019	0.0054	0.0028	0.0055
		(1.58)	(−2.30)	(−3.02)	(−1.24)	(1.59)	(1.06)	(1.35)	(1.23)
Internet & Catalog Retail	255020	−0.0015	0.0048	0.0072	0.0092	0.0001	−0.0007	−0.0001	−0.0008
		(−1.22)	(3.41)	(1.38)	(2.03)	(0.13)	(−0.28)	(−0.04)	(−0.30)
Multiline Retail	255030	−0.0024	0.0038	0.0016	−0.0015	0.0007	0.0016	0.0060	−0.0018
		(−0.22)	(0.92)	(0.19)	(−0.79)	(0.09)	(2.05)	(1.20)	(−0.41)
Specialty Retail	255040	0.0011	−0.0022	−0.0070	0.0030	−0.0002	0.0000	0.0004	0.0010
		(0.86)	(−1.28)	(−2.22)	(3.53)	(−0.25)	(0.05)	(0.19)	(0.72)
Food & Staples Retailing	301010	0.0009	0.0002	0.0016	−0.0014	0.0000	−0.0008	0.0009	−0.0012
		(0.80)	(0.41)	(2.09)	(−0.99)	(−0.01)	(−0.87)	(0.86)	(−0.56)
Beverages	302010	−0.0027	−0.0031	−0.0021	−0.0020	0.0029	0.0012	−0.0109	−0.0003
		(−1.21)	(−3.07)	(−0.94)	(−1.14)	(1.50)	(0.78)	(−1.60)	(−0.13)

(*continued on next page*)

Table A.3 (*continued*)

Industry	GICS Code	Left 5% Temp Tail ×2				Right 5% Temp Tail ×2			
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Food Products	302020	−0.0006	0.0003	−0.0001	−0.0008	−0.0007	−0.0017	0.0018	−0.0019
		(−0.40)	(0.46)	(−0.09)	(−0.60)	(−0.30)	(−1.26)	(0.92)	(−0.97)
Tobacco	302030	−0.0029	−0.0003	0.0017	−0.0018	0.0013	−0.0084	−0.0009	−0.0018
		(−1.86)	(−0.16)	(0.85)	(−1.07)	(1.01)	(−1.18)	(−0.30)	(−0.74)
Personal Products	303020	−0.0015	−0.0010	0.0059	0.0049	0.0004	0.0014	−0.0001	0.0035
		(−0.85)	(−2.10)	(3.15)	(1.45)	(0.54)	(2.79)	(−0.02)	(1.29)
Health Care Equipment & Supplies	351010	0.0008	0.0004	0.0014	−0.0009	0.0000	0.0017	0.0002	−0.0001
		(1.95)	(0.79)	(2.83)	(−1.10)	(0.02)	(3.04)	(0.29)	(−0.24)
Health Care Providers & Services	351020	0.0005	−0.0003	0.0017	0.0005	0.0000	0.0007	−0.0006	0.0005
		(0.89)	(−0.63)	(1.25)	(0.63)	(−0.04)	(0.99)	(−0.63)	(0.47)
Health Care Technology	351030	−0.0010	−0.0008	−0.0007	0.0046	0.0023	−0.0008	0.0042	0.0013
		(−0.66)	(−1.03)	(−0.15)	(1.40)	(1.34)	(−0.22)	(0.95)	(0.89)
Biotechnology	352010	−0.0026	0.0003	−0.0011	0.0008	0.0019	−0.0022	0.0001	0.0005
		(−1.24)	(0.24)	(−0.46)	(0.48)	(1.10)	(−1.12)	(0.07)	(0.15)
Pharmaceuticals	352020	0.0015	−0.0050	−0.0094	−0.0007	−0.0082	−0.0021	−0.0011	0.0010
		(0.32)	(−2.55)	(−2.85)	(−0.73)	(−1.53)	(−1.08)	(−0.48)	(0.67)
Life Sciences Tools & Services	352030	0.0008	0.0031	0.0002	0.0005	−0.0004	−0.0005	−0.0017	−0.0009
		(0.45)	(2.35)	(0.22)	(0.81)	(−0.19)	(−0.20)	(−0.65)	(−1.55)
Banks	401010	−0.0004	−0.0006	−0.0019	0.0004	−0.0010	−0.0012	−0.0027	0.0003
		(−0.45)	(−0.64)	(−2.78)	(0.21)	(−1.11)	(−1.29)	(−3.66)	(0.10)
Thrifts & Mortgage Finance	401020	−0.0019	−0.0023	−0.0044	−0.0023	−0.0009	−0.0010	−0.0004	0.0016
		(−0.55)	(−2.46)	(−1.06)	(−0.64)	(−0.57)	(−1.56)	(−0.16)	(0.51)
Diversified Financial Services	402010	0.0026	−0.0036	−0.0052	−0.0042	−0.0025	−0.0014	0.0162	0.0361
		(0.48)	(−1.51)	(−0.60)	(−0.15)	(−0.44)	(−1.33)	(2.08)	(0.74)
Consumer Finance	402020	−0.0109	0.0139	−0.0200	−0.0206	0.0051	−0.0174	−0.0018	−0.0224
		(−0.70)	(0.95)	(−1.25)	(−1.91)	(0.50)	(−1.33)	(−0.16)	(−1.21)
Capital Markets	402030	0.0012	0.0017	0.0010	0.0013	0.0016	0.0011	−0.0011	0.0032
		(1.63)	(2.23)	(0.77)	(1.06)	(1.89)	(1.07)	(−0.97)	(2.90)
Insurance	403010	0.0005	−0.0001	−0.0015	0.0014	0.0000	0.0016	−0.0009	0.0000
		(0.30)	(−0.06)	(−1.16)	(0.63)	(0.07)	(0.89)	(−0.79)	(0.03)
Real Estate Investment Trusts	404020	−0.0043	0.0014	0.0077	0.0311	0.0040	−0.0175	−0.0050	0.0030
(REITs)		(−1.46)	(0.19)	(1.58)	(1.11)	(0.61)	(−1.33)	(−0.92)	(0.10)
Internet Software & Services	451010	0.0015	−0.0027	0.0013	0.0028	0.0006	0.0049	−0.0004	0.0020
		(1.30)	(−3.24)	(0.79)	(0.90)	(1.18)	(2.46)	(−0.31)	(0.41)
IT Services	451020	−0.0006	−0.0008	−0.0010	−0.0003	0.0005	0.0005	0.0005	0.0026
		(−0.49)	(−2.08)	(−0.92)	(−0.33)	(1.02)	(0.57)	(0.58)	(1.33)
Software	451030	−0.0047	0.0000	−0.0004	−0.0035	−0.0013	0.0010	0.0000	−0.0006
		(−2.64)	(−0.04)	(−0.65)	(−3.33)	(−2.67)	(0.69)	(0.04)	(−0.57)
Communications Equipment	452010	−0.0005	−0.0004	−0.0017	0.0004	0.0031	−0.0005	−0.0007	−0.0001
		(−0.46)	(−1.30)	(−1.86)	(0.70)	(2.19)	(−0.86)	(−1.44)	(−0.13)
Tech. Hardware, Storage &	452020	0.0011	0.0016	0.0004	0.0039	−0.0039	0.0040	0.0013	−0.0040
Peripherals		(0.55)	(0.54)	(0.15)	(0.82)	(−2.00)	(1.20)	(0.83)	(−1.53)
Electronic Equipment &	452030	−0.0020	−0.0017	−0.0012	0.0004	−0.0001	−0.0005	−0.0004	0.0011
Components		(−1.73)	(−2.53)	(−1.91)	(0.57)	(−0.08)	(−0.66)	(−0.54)	(0.94)
Semiconductors & Equipment	453010	0.0002	−0.0002	−0.0024	−0.0008	−0.0004	−0.0007	0.0015	0.0007
		(0.30)	(−0.46)	(−1.13)	(−0.86)	(−0.48)	(−1.01)	(1.08)	(0.99)
Diversified Telecomm. Services	501010	−0.0054	−0.0007	−0.0046	0.0012	0.0008	−0.0059	0.0040	0.0020
		(−1.01)	(−0.14)	(−0.91)	(0.28)	(0.18)	(−1.19)	(0.92)	(0.46)
Wireless Telecomm. Services	501020	−0.0145	−0.0019	0.0035	−0.0092	0.0035	0.0085	0.0078	0.0044
		(−1.94)	(−0.13)	(0.48)	(−1.85)	(0.32)	(1.29)	(0.88)	(0.49)
Electric Utilities	551010	0.0009	0.0002	−0.0021	0.0005	−0.0010	0.0008	0.0012	−0.0001
		(1.70)	(0.42)	(−3.22)	(1.08)	(−4.40)	(2.27)	(2.22)	(−0.18)
Gas Utilities	551020	0.0006	0.0062	−0.0005	0.0025	0.0026	−0.0033	−0.0022	0.0015
		(0.49)	(2.53)	(−0.47)	(1.34)	(2.02)	(−0.94)	(−1.86)	(1.25)
Multi-Utilities	551030	0.0005	−0.0006	0.0012	0.0001	0.0000	0.0015	−0.0007	0.0001
		(1.02)	(−0.82)	(1.27)	(0.15)	(−0.08)	(2.35)	(−0.57)	(0.21)
Ind. Power & Renewable	551050	−0.0039	0.0138	−0.0217	−0.0361	−0.0110	0.0136	−0.0242	−0.0416
Electricity Prod.		(−0.27)	(0.94)	(−2.02)	(−1.63)	(−2.40)	(1.78)	(−1.53)	(−1.37)

revenues that accrue from foreign operations, in both levels and interacted with each of the Chebyshev polynomial coefficients, as additional control variables. We then conduct Wald tests on the interaction terms and find that in about 85% of industry-quarters, the earnings-temperature response functions are not statistically different from the baseline (see Internet Appendix Table IA1 for test statistics and *p*-values). In the remaining set of cases, we examine the economic significance of the difference in earnings impacts after accounting for firms' international exposures.

We find that the economic magnitudes associated with international exposures are very small. For example, the average change in the earnings impact associated with a doubling of the extreme 5% right (left) tail of the tempera-

Table A.4
SafeGraph establishment visits and extreme temperature events, OLS regressions. This table reports OLS fixed effects regressions of the natural log of one plus daily establishment visits on extreme temperature days. The sample includes SafeGraph establishments with 2-digit NAICS codes of 71–72 with daily visit data in April, May, and June of 2018 to 2021. We define extreme temperature days (temp shock day indicator) as days on which firms are exposed to temperatures below 4°C, the critical threshold for which we find a statistically significant negative effect on Q2 Hotels & Restaurants profitability in Table 2. In Panel B, we interact the temp shock day indicator with a weekend indicator, equal to one on Friday, Saturdays, and Sundays, and zero otherwise. All regressions include quarter-by-establishment fixed effects and place-by-day-of-week fixed effects. In both panels, column 1 includes the full sample of observations. In columns 2 to 6, we focus on subsamples of establishments within 4-digit NAICS classifications. All regressions include controls for mean daily temperature and linear and squared daily precipitation. *t*-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering at the quarter-by-establishment level.

	Panel A: Baseline OLS regressions					
	NAICS 71–72 Full Sample (1)	NAICS 7112 Spectator Sports (2)	NAICS 7121 Museums & Historical Places (3)	NAICS 7132 Gambling Establishments (4)	NAICS 7224 Drinking Places (Beverages) (5)	NAICS 7225 Restaurants (6)
Temp shock day	−0.0267	−0.0151	−0.0552	−0.0294	−0.0252	−0.0201
	(−104.62)	(−2.74)	(−84.77)	(−4.56)	(−23.85)	(−70.32)
Mean temp (°C)	0.0090	0.0113	0.0082	0.0163	0.0091	0.0091
	(456.32)	(24.65)	(158.65)	(29.36)	(113.45)	(414.72)
Precipitation (mm)	−0.0008	−0.0023	−0.0035	0.0008	−0.0002	−0.0003
	(−101.77)	(−14.21)	(−144.25)	(4.59)	(−7.01)	(−31.78)
Adj. R^2	0.795	0.761	0.785	0.846	0.736	0.799
N	233,172,203	1,147,105	37,459,200	683,536	14,960,184	178,922,178
Squared precip. control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr X Place FE	Yes	Yes	Yes	Yes	Yes	Yes
Place X Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B: OLS regressions with weekend interactions					
	NAICS 71–72 Full Sample (1)	NAICS 7112 Spectator Sports (2)	NAICS 7121 Museums & Historical Places (3)	NAICS 7132 Gambling Establishments (4)	NAICS 7224 Drinking Places (Beverages) (5)	NAICS 7225 Restaurants (6)
Temp shock day	−0.0187	0.0009	−0.0568	−0.0027	−0.0098	−0.0105
	(−71.53)	(0.16)	(−84.03)	(−0.42)	(−9.13)	(−35.85)
Temp shock day X Weekend	−0.0200	−0.0401	0.0040	−0.0639	−0.0379	−0.0241
	(−81.78)	(−7.28)	(6.47)	(−14.46)	(−37.84)	(−87.82)
Adj. R^2	0.795	0.761	0.785	0.846	0.736	0.799
N	233,172,203	1,147,105	37,459,200	683,536	14,960,184	178,922,178
Mean temp. control	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr X Place FE	Yes	Yes	Yes	Yes	Yes	Yes
Place X Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Place X Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5
SafeGraph establishment visits and extreme temperature events, Alternative weekend. This table reports Poisson fixed effects regressions of daily establishment visits on extreme temperature days. The sample includes SafeGraph establishments with 2-digit NAICS codes of 71–72 with daily visit data in April, May, and June of 2018 to 2021. We define extreme temperature days (temp shock day indicator) as days on which firms are exposed to temperatures below 4°C, the critical threshold for which we find a statistically significant negative effect on Q2 Hotels & Restaurants profitability in Table 2. We interact the temp shock day indicator with a weekend indicator, equal to one on Saturdays and Sundays, and zero otherwise. All regressions include quarter-by-establishment fixed effects and place-by-day-of-week fixed effects. Column 1 includes the full sample of observations. In columns 2 to 6, we focus on subsamples of establishments within 4-digit NAICS classifications. All regressions include controls for mean daily temperature and linear and squared daily precipitation. *z*-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering at the quarter-by-establishment level.

	Poisson regressions with alternatively defined weekend interactions					
	NAICS 71–72 Full Sample (1)	NAICS 7112 Spectator Sports (2)	NAICS 7121 Museums & Historical Places (3)	NAICS 7132 Gambling Establishments (4)	NAICS 7224 Drinking Places (Beverages) (5)	NAICS 7225 Restaurants (6)
Temp shock day	−0.0428	−0.0358	−0.0767	−0.0143	−0.0492	−0.0289
	(−27.16)	(−2.20)	(−14.29)	(−1.13)	(−9.06)	(−29.81)
Temp shock day X Weekend	−0.0303	−0.0863	−0.0470	−0.0342	−0.0172	−0.0228
	(−23.85)	(−3.38)	(−11.84)	(−3.48)	(−4.10)	(−25.78)
Pseudo R^2	0.751	0.719	0.815	0.891	0.674	0.698
N	233,172,203	1,147,105	37,459,200	683,536	14,960,184	178,922,178
Mean temp. control	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr × Place FE	Yes	Yes	Yes	Yes	Yes	Yes
Place × Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.6

Quarterly Sensitivity of Industry Earnings to Extreme Cold and Heat, Weekday Temperatures. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2), but with weather only on weekdays (Monday to Friday). We focus on industries with a statistically significant relation between earnings and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (+,−8°) Trading Cos. & Distributors (+,−1°) Software (−, −4°)	Machinery (+,−5°) Textile, Apparel & Lux. (−, 2°) Beverages (−, 10°) Personal Products (−, 2°) Life Science Tools (+,−1°) Gas Utilities (+,10°)	Leisure Products (+,8°) Software (−, 6°)	Specialty Retail (+,4°) IT Services (−, −9°) Software (−, −2°)
Heat Shock Sensitivity	Oil, Gas & Fuels (−, 23°) Paper & Forest Products (+,20°) Trading Cos. & Distributors (+,24°) Technology Hardware (−, 21°) Electric Utilities (−, 21°)	Construction Materials (+,30°) Leisure Products (−, 29°) Personal Products (+,33°) Health Care Equip. (+,29°) Technology Hardware (+,36°)	Technology Hardware (+,35°) Electric Utilities (+,34°)	Metals & Mining (+,26°) Trading Cos. & Distributors (−, 26°)

ture distribution is just 0.39 (−2.18) basis points. Of the 32 industry-calendar quarters that we find to have a significant temperature-earnings relation, only 4 have response functions that are significantly different after accounting for geographic segments (machinery in Q4, beverages in Q2, and capital markets in Q3 and Q4). However, the economic magnitudes associated with international exposures are again tiny, averaging just 4.80 basis points for a doubling of the extreme 5% tail. Overall, this suggests that the earnings-temperature sensitivity of firms in our sample does not appear to be greatly affected by missing weather and location data for firms' international establishments.

A2. Hedging

The second caveat is that the temperature effects we document are likely to be net of firms' hedging activities. While we believe these net magnitudes are interesting in their own right, we also try to isolate the direct effect of extreme temperatures on corporate profitability. Since data on firm-level temperature hedging is not available, we instead exploit the natural experiment setting of Purnanandam and Weagley (2016), in which the CME Group introduced city-specific weather derivative contracts in a staggered fashion. We conduct a difference-in-difference analysis to disentangle the gross effects of temperature exposures on corporate profitability from the potential for hedging these exposures. Specifically, we collect city-specific weather derivative introduction and discontinuation dates from the CME Group, as well as the geographic coordinates of the weather stations used to determine payouts for each contract. Each fiscal quarter, we classify each of a given firm's establishments as having the potential to hedge temperature risk if the establishment is within 100 miles of a weather station for a traded weather contract. Finally, we calculate a firm-level hedging potential measure by taking the sales-weighted average of the hedging potential indicators across firm's establishments each fiscal quarter.

We include the firm-level hedging potential measure in our baseline earnings regressions, in both levels and interacted with the Chebyshev coefficients. We conduct Wald tests on the interaction terms and find that in over 81% of industry-quarters, the earnings-temperature response functions are not statistically different from the baseline (see Internet Appendix Table IA1). In the remaining set of cases, we examine the economic significance of the difference in earnings impacts of extreme temperatures when accounting for firms' hedging potential. We find that the economic magnitudes associated with hedging are very small. For example, the average change in the earnings impact associated with a doubling of the extreme 5% right (left) tail of the temperature distribution is just 0.18 (2.00) basis points relative to mean earnings.

Of the 32 industry-calendar quarters that we find to have a significant temperature-earnings relation, just 4 have response functions that are significantly different after accounting for hedging (trading companies and distributors in Q1, leisure products in Q1, personal products in Q2, and electric utilities in Q2). However, the economic magnitudes associated with hedging are again relatively small, averaging just 6.93 basis points of mean earnings for a doubling of the extreme 5% tails. Overall, this suggests that the earnings-temperature sensitivity of firms in our sample does not appear to respond to their potential to hedge temperature risk as captured by proximity to

Table A.7
Industry Classifications. This table reports classifications of industries on the basis of tradability and heat sensitivity. Tradability is based on the classifications of Mian and Sufi (2014). Heat sensitivity is based on the sector classifications of Graff-Zivin and Neidell (2014).

		Industry Classification	
Industry	GICS Code	Tradability	Heat Sensitivity
Energy Equipment & Services	101010	Non-Tradable	Non-Sensitive
Oil, Gas & Consumable Fuels	101020	Tradable	Non-Sensitive
Chemicals	151010	Tradable	Non-Sensitive
Construction Materials	151020	Tradable	Non-Sensitive
Containers & Packaging	151030	Tradable	Non-Sensitive
Metals & Mining	151040	Tradable	Heat-Sensitive
Paper & Forest Products	151050	Tradable	Heat-Sensitive
Aerospace & Defense	201010	Tradable	Non-Sensitive
Building Products	201020	Tradable	Non-Sensitive
Construction & Engineering	201030	Non-Tradable	Heat-Sensitive
Electrical Equipment	201040	Tradable	Non-Sensitive
Machinery	201060	Tradable	Non-Sensitive
Trading Companies & Distributors	201070	Non-Tradable	Non-Sensitive
Commercial Services & Supplies	202010	Non-Tradable	Non-Sensitive
Professional Services	202020	Non-Tradable	Non-Sensitive
Air Freight & Logistics	203010	Non-Tradable	Heat-Sensitive
Airlines	203020	Non-Tradable	Heat-Sensitive
Road & Rail	203040	Non-Tradable	Heat-Sensitive
Auto Components	251010	Tradable	Non-Sensitive
Household Durables	252010	Tradable	Non-Sensitive
Leisure Products	252020	Tradable	Non-Sensitive
Textiles, Apparel & Luxury Goods	252030	Tradable	Non-Sensitive
Hotels, Restaurants & Leisure	253010	Non-Tradable	Non-Sensitive
Diversified Consumer Services	253020	Non-Tradable	Non-Sensitive
Media	254010	Other	Non-Sensitive
Internet & Catalog Retail	255020	Tradable	Non-Sensitive
Multiline Retail	255030	Non-Tradable	Non-Sensitive
Specialty Retail	255040	Non-Tradable	Non-Sensitive
Food & Staples Retailing	301010	Non-Tradable	Non-Sensitive
Beverages	302010	Tradable	Non-Sensitive
Food Products	302020	Tradable	Heat-Sensitive
Tobacco	302030	Tradable	Heat-Sensitive
Personal Products	303020	Tradable	Non-Sensitive
Health Care Equipment & Supplies	351010	Tradable	Non-Sensitive
Health Care Providers & Services	351020	Non-Tradable	Non-Sensitive
Health Care Technology	351030	Tradable	Non-Sensitive
Biotechnology	352010	Tradable	Non-Sensitive
Pharmaceuticals	352020	Tradable	Non-Sensitive
Life Sciences Tools & Services	352030	Non-Tradable	Non-Sensitive
Banks	401010	Non-Tradable	Non-Sensitive
Thrifts & Mortgage Finance	401020	Non-Tradable	Non-Sensitive
Diversified Financial Services	402010	Non-Tradable	Non-Sensitive
Consumer Finance	402020	Non-Tradable	Non-Sensitive
Capital Markets	402030	Non-Tradable	Non-Sensitive
Insurance	403010	Tradable	Non-Sensitive
Real Estate Investment Trusts (REITs)	404020	Other	Non-Sensitive
Internet Software & Services	451010	Other	Non-Sensitive
IT Services	451020	Non-Tradable	Non-Sensitive
Software	451030	Tradable	Non-Sensitive
Communications Equipment	452010	Tradable	Non-Sensitive
Tech. Hardware, Storage & Peripherals	452020	Tradable	Non-Sensitive
Electronic Equipment & Components	452030	Tradable	Heat-Sensitive
Semiconductors & Equipment	453010	Non-Tradable	Non-Sensitive
Diversified Telecomm. Services	501010	Non-Tradable	Non-Sensitive
Wireless Telecomm. Services	501020	Non-Tradable	Non-Sensitive
Electric Utilities	551010	Non-Tradable	Heat-Sensitive
Gas Utilities	551020	Non-Tradable	Heat-Sensitive
Multi-Utilities	551030	Non-Tradable	Heat-Sensitive
Ind. Power & Renewable Electricity Prod.	551050	Non-Tradable	Heat-Sensitive

Table A.8

Quarterly Sensitivity of Industry Earnings (including Extraordinary Items) to Extreme Cold and Heat. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2). We focus on industries with a statistically significant relation between earnings (including extraordinary items) and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings (including extraordinary items).

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Construction Materials (−, −9°) Aerospace & Defense (+,−10°) Trading Cos. & Distributors (+,−3°) Diversified Consumer Services (−, −5°) Media (+,−10°) Software (−, −4°) Gas Utilities (+,−12°) Hotels & Restuarants (−, −2°) Personal Products (−, −3°) Pharmaceuticals (−, 6°)	Oil, Gas & Fuels (+,5°) Building Products (−, −2°) Construction & Eng. (+,−1°) Commercial Serv. & Supplies (+,−10°) Airlines (−, −7°) Households Durables (+,−9°) Textile, Apparel & Lux. (−, 2°)	Paper & Forest Products (−, 6°) Construction & Eng. (+,8°) Air Freight & Logistics (+,11°) Specialty Retail (−, 12°) Electric Utilities (−, 13°) Software (−, −1°) IT Services (−, −9°)	Building Products (+,−5°) Diversified Consumer Services (+,1°) Hotels & Restuarants (+,−10°) Personal Products (+,3°) Consumer Finance (+,−9°)
Heat Shock Sensitivity	Paper & Forest Products (+,20°) Commercial Serv. & Supplies (+,21°) Personal Products (+,22°)	Construction Materials (+,31°) Health Care Equip. (+,28°) Technology Hardware (+,30°)	Metals & Mining (+,32°) Construction & Eng. (−, 34°) Personal Products (−, 35°) Capital Markets (−, 34°) Electric Utilities (+,36°)	Metals & Mining (+,28°) Electrical Equipment (+,27°) Trading Cos. & Distributors (−, 26°) Machinery (−, 25°) Airlines (+,24°) Capital Markets (+,26°)

locations with weather derivatives. This finding is consistent with those of Till (2015), who documents that most temperature derivative contracts offered by the CME have zero open interest. Consequently, the CME has progressively scaled back its offering of temperature contracts to just 8 U.S. locations in 2018, down from a high of 24 in 2008.

A3. Adaptations

In our final set of robustness tests, we consider the possibility that firms operating in relatively hotter areas of the U.S. may exhibit temperature sensitivity that differs from their counterparts with geographic footprints predominantly in cooler parts of the country. To test this conjecture, within each industry, we split the sample of firms into north and south subsamples. Specifically, we calculate the centroid of each firm's geographic footprint, weighting each establishment by its share of firm sales in a given year. We calculate industry-specific latitude cutoffs such that half of firms lie to the north of the cutoff and the other half to the south. We then define a north/south indicator variable and include this variable as an interaction with each of the Chebyshev polynomial coefficients. By including these interactions, we can then understand whether the earnings-temperature relationship differs between firms with more north vs. south-based operations within a given industry and calendar quarter.

To this end, we conduct Wald tests on the interaction terms and find that in about 85% of industry-quarters, the earnings-temperature response functions are not statistically different (see Internet Appendix Table IA1). In the remaining set of cases, we examine the economic significance of the difference in earnings impacts of extreme temperatures when accounting for firms' north/south locations. We find that the economic magnitudes associated with firms' north/south locations show an interesting pattern. In particular, firms with geographic footprints centered in the northern (southern) U.S. tend to be more sensitive to extreme heat (cold). However, within an industry, the economic magnitudes are relatively modest. For example, the average change in the earnings impact associated with a doubling of the extreme 5% right (left) tail of the temperature distribution is about 2.64 (13.75) basis points. Of the 32 industry-calendar quarters that we find to have a significant temperature-earnings relation, 4 have response functions that significantly differ between northern and southern firms (trading companies and distributors in Q1, leisure products in Q3, personal products in Q2, and IT services in Q4). The economic magnitudes associated with

Table A.9

Quarterly Sensitivity of Industry Earnings (including Extraordinary and Special Items) to Extreme Cold and Heat. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2). We focus on industries with a statistically significant relation between earnings (including extraordinary and special items) and extreme temperature exposure (at the 5% level). + (-) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly earnings (including extraordinary and special items).

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Construction Materials ($-$, -9°) Aerospace & Defense (+, -11°) Trading Cos. & Distributors (+, -3°) Diversified Consumer Services ($-$, -7°) Software ($-$, -5°) Gas Utilities (+, -12°)	Oil, Gas & Fuels (+, 7°) Commercial Serv. & Supplies (+, -9°) Households Durables (+, -5°) Hotels & Restuarants ($-$, -3°) Textile, Apparel & Lux. ($-$, 1°) Pharmaceuticals ($-$, 7°)	Metals & Mining ($-$, 8°) Construction & Eng. (+, 4°) Leisure Products (+, 9°) Specialty Retail ($-$, 11°)	Oil, Gas & Fuels (+, -3°) Construction Materials (+, -6°) Hotels & Restuarants (+, -6°) Specialty Retail (+, 3°) Personal Products (+, -3°) Consumer Finance (+, -10°) Software ($-$, -2°) IT Services ($-$, -9°)
Heat Shock Sensitivity	Paper & Forest Products (+, 20°) Trading Cos. & Distributors (+, 25°)	Metals & Mining (+, 31°) Health Care Equip. (+, 28°) Multi-Utilities (+, 28°)	Metals & Mining (+, 31°) Construction & Eng. ($-$, 34°) Air Freight & Logistics ($-$, 33°) Capital Markets ($-$, 35°) Electric Utilities (+, 35°)	Electrical Equipment (+, 27°) Trading Cos. & Distributors ($-$, 25°) Machinery ($-$, 25°) Pharmaceuticals (+, 24°) Capital Markets (+, 24°)

Table A.10

Quarterly Sensitivity of Industry Operating Cash Flows to Extreme Cold and Heat. This table reports directional marginal effects and critical temperature threshold estimates for GICS six-digit industries exhibiting sensitivity to extreme temperatures. Estimates are based on regression Eq. (2). We focus on industries with a statistically significant relation between operating cash flows (EPS including extraordinary and special items plus depreciation and amortization and deferred taxes) and extreme temperature exposure (at the 5% level). + ($-$) indicates that exposure to extreme temperatures increases (decreases) earnings. Critical temperature thresholds are reported in degrees Celsius and represent the temperature below (above) which abnormal exposure to cold (heat) is associated with a statistically significant marginal effect on quarterly operating cash flows.

	Q1	Q2	Q3	Q4
Cold Shock Sensitivity	Aerospace & Defense (+, -9°) Trading Cos. & Distributors (+, -5°) Diversified Consumer Services ($-$, -6°) Communications Equipment ($-$, -10°) Electric Utilities (+, -8°)	Construction Materials ($-$, -6°) Construction & Eng. (+, -1°) Households Durables (+, -1°) Hotels & Restuarants ($-$, -7°) Pharmaceuticals ($-$, 8°)	Energy Equipment & Services (+, 14°) Leisure Products (+, 8°) Personal Products (+, 12°)	Specialty Retail (+, 1°) Personal Products ($-$, 0°) Software ($-$, -2°)
Heat Shock Sensitivity	Chemicals ($-$, 19°) Paper & Forest Products (+, 23°)	Construction Materials (+, 31°) Auto Components ($-$, 27°) Multi-Utilities (+, 28°)	Air Freight & Logistics ($-$, 33°) Personal Products ($-$, 34°) Capital Markets ($-$, 36°) Electric Utilities (+, 34°)	Metals & Mining (+, 24°) Machinery ($-$, 24°) Electrical Equipment (+, 26°) Trading Cos. & Distributors ($-$, 25°) Air Freight & Logistics ($-$, 32°) Food & Staples Retailing (+, 27°) Personal Products ($-$, 22°) Health Care Tech. (+, 25°) Pharmaceuticals (+, 24°) Consumer Finance (+, -11°)

these differences are, on average, about a 22 basis point change in profitability for a doubling of the extreme 5% tail. Overall, our evidence suggests that the effects of extreme temperatures on earnings do not vary considerably across northern vs. southern firms in the majority of industries. However, in these 4 industries, we find that the effects are economically important and statistically different.

Appendix B. Mechanisms driving temperature sensitivities

In this appendix section, we discuss additional tests aimed at understanding the importance of the heating/cooling and labor productivity channels in explaining our main results.

B1. Heating/cooling channel

To understand the importance of a heating/cooling channel, we use data on electricity usage from the U.S. Energy Information Administration (EIA). These data provide monthly commercial and industrial electricity sales (in dollars per customer) at the utility level from 1990 to 2015. We combine these data with a utility-zip code mapping compiled by the U.S. Department of Energy's National Renewable Energy Laboratory. We then match average electricity costs among a given utility's commercial and industrial (i.e., non-residential) customers with establishments in our data by zip codes serviced by the utility in a given month. For zip codes covered by multiple utilities, we assign a weighted average of electricity costs. For zip codes not covered by one of the utilities in the EIA data, we assign state-level averages of costs each month.

Armed with average zip code electricity costs for each establishment in our dataset, we calculate a firm-level electricity cost measure in the same way as our main temperature exposure variables. Specifically, each fiscal quarter, we take a sales-weighted average of these measures across a firm's establishments. We then examine whether fluctuations in electricity costs can account for the industry-level relations between temperature exposure and profitability in our baseline tests. In particular, we include the firm-level electricity cost measure in our industry-calendar quarter earnings specifications, both in levels and interacted with each of the Chebyshev polynomial coefficients.

We conduct a Wald test on the estimated interaction coefficients to examine the extent to which the earnings-temperature relationship is driven by variation in electricity costs. We find that of the 32 industry-calendar quarters with a significant extreme temperature-earnings relation, 25% have response functions that are significantly different after accounting for electricity costs. The economic magnitude associated with this channel is relatively modest, with an average earnings impact of 14.1 basis points for a doubling of the extreme 5% tails. This accounts for about one third of the overall economic effect of extreme temperature shocks among these 8 industries (oil and gas, metals and mining, construction and engineering, leisure products, hotels and restaurants, specialty retail, beverages, and life science tools).

B2. Labor productivity channel

We also examine the potential of a labor productivity channel using additional data. Specifically, we test whether fluctuations in the frequency of work-related injuries and illnesses can explain the earnings-temperature relationships we document. We collect additional data on work-related injuries and illnesses at the industry-state level from the Bureau of Labor Statistics' Survey of Occupational Injuries and Illnesses (BLS SOII). This survey provides annual estimates of work-related injury and illness incidence rates from 1996 to 2014.[20] We match these rates with firm establishments in our sample based on state and industry, and then calculate a sales-weighted average incidence rate across a firm's establishments each quarter.[21]

As with the electricity usage data, we add the firm-level injury and illness incidence rates to our baseline earnings specifications, in both levels and interacted with the Chebyshev polynomial coefficients. Finally, we conduct a series of Wald tests for each industry-calendar quarter regression to understand the degree to which the effects of temperature exposure on corporate profitability can be attributed to a labor productivity channel proxied by work-related injuries and illnesses. Of the 32 industry-calendar quarters that we find to have a significant temperature-earnings relation, 4 (aerospace and defense, machinery, leisure products, and textiles, apparel & luxury goods) have response functions that are significantly different after accounting for illness and injuries. The economic magnitudes associated with this channel are relatively important, averaging 25.9 basis points of mean earnings for a doubling of the extreme 5% tails. Among these 4 industries, this amounts to about 70% of the overall economic effect associated with doubling the extreme tails.

Appendix C. Heterogeneity across analysts and investors

C1. Analyst forecast results

In columns 2 and 3 of Table C.1, we examine how analysts' locations affect their responsiveness to extreme temperature events (for comparison, column 1 presents the unconditional baseline estimate). Our conjecture is that

[20] We acknowledge that our analysis using the BLS SOII data should be treated as exploratory due to data limitations. In particular, the publicly available version of the work-related injuries and illnesses dataset contains annual data at the state-industry level. This is much more aggregated than our main dataset, which is at the quarterly establishment level. More definitive tests involving BLS SOII establishment level data would require restricted access to the BLS database and may be a topic for future research.

[21] The BLS SOII industry variables are classified by SIC code before 2002 and by NAICS code from 2002 onward. In order to merge these variables with the GICS codes in our main data, we first convert the 4, 5, and 6-digit SIC codes in the BLS data before 2002 into 4-digit NAICS codes. We then match the 4-digit BLS NAICS data with 2-digit GICS codes in our main dataset based on the concordance provided by Alison Weingarden from the Federal Reserve Board. The link file is available at: https://sites.google.com/site/alisonweingarden/links/industries.

Table C.1
Change in analyst mean consensus forecasts surrounding extreme temperature events. This table reports estimates of changes in analysts' consensus quarterly EPS forecasts (scaled by beginning-of-quarter share price) surrounding extreme temperature events over several event windows. We define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. For each event window, we compare the average consensus forecasts in the pre- vs. post-event windows. We multiply forecasts for temperature events associated with a positive effect on earnings by negative one and then demean forecasts within each event window. In column 1, we consider all analyst forecasts in our sample. In columns 2 and 3, we examine how analysts' locations affect their responsiveness to extreme temperature events. We collect analyst location data from Nelson's Directory of Investment Research, as outlined by Malloy (2005). We match this location data with establishment-level temperature exposures. We then classify analysts as those that are located near the source of a firm-level temperature shock (i.e., within 100 miles of an establishment that drives the firm-level temperature extreme on a given day) or not. In columns 4 and 5, we classify analysts as experienced with past temperature shocks if they have previously covered a firm that experienced an extreme temperature event during our sample. In columns 6 and 7, we classify analysts as experienced with past temperature shocks if they covered any firm in the same GICS industry during the same quarter that a firm in the industry experienced an extreme temperature event. In columns 8 and 9, we match analyst locations with county-level public climate change opinion estimates from the Yale Program on Climate Change Communication to classify analysts as being located in counties that are receptive to climate change versus those in locations that are opposed to the idea. Finally, in columns 10 and 11, we use data on analysts' political contributions to party-affiliated committees in order to classify their political preferences. We then calculate Republican and Democrat consensus forecasts for the days surrounding a subset of extreme temperature events in our sample. t-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering across events within the same fiscal quarter.

	All analyst	Located near shock?		Exp. past firm shock?		Exp. past ind. shock?		Local climate views		Political affiliation	
Event window (days)	observations (1)	Yes (2)	No (3)	Yes (4)	No (5)	Yes (6)	No (7)	Anti-CC (8)	Pro-CC (9)	Republican (10)	Democrat (11)
[−120,+20]	0.003	0.034	0.009	0.031	0.014	0.023	0.031	−0.005	−0.019	−0.008	−0.044
	(0.10)	(0.82)	(0.28)	(0.97)	(0.67)	(0.78)	(0.98)	(−0.16)	(−0.51)	(−0.16)	(−0.29)
[−110,+10]	0.007	0.035	0.022	0.028	0.009	0.020	0.029	−0.000	−0.011	−0.033	−0.027
	(0.30)	(1.06)	(0.85)	(1.10)	(0.59)	(0.85)	(1.11)	(−0.01)	(−0.38)	(−0.90)	(−0.19)
[−15,+5]	0.005	0.031	0.023	0.028	0.003	0.021	0.016	0.005	−0.007	−0.009	−0.008
	(0.23)	(1.32)	(0.96)	(1.21)	(0.25)	(1.01)	(0.72)	(0.21)	(−0.25)	(−0.31)	(−0.06)
[−11,+1]	0.007	0.026	0.027	0.029	0.009	0.022	0.019	0.008	−0.003	−0.003	−0.055
	(0.37)	(1.20)	(1.19)	(1.33)	(0.67)	(1.14)	(0.82)	(0.37)	(−0.10)	(−0.12)	(−0.53)
N events	8,584	2,406	5,546	7,168	6,401	8,026	4,519	8,214	5,280	1,935	1,685

analysts who are located in areas affected by temperature shocks may be more likely to update their forecasts for firms with local operations. This hypothesis is motivated by the findings of Malloy (2005), who demonstrates that geographically proximate analysts issue more accurate forecasts. We collect analyst location data from Nelson's Directory of Investment Research, as outlined by Malloy (2005). We match this location data with establishment-level temperature exposures. We then classify analysts as local and non-local, based on whether they are located near the source of a firm-level temperature shock (i.e., within 100 miles of an establishment that drives the firm-level temperature extreme on a given day) or not. For each group of analysts, we calculate separate consensus forecasts and examine whether analysts who are located near the source of firm-level temperature shocks exhibit greater responsiveness to extreme temperature events. Contrary to our conjecture, we find no such evidence. Specifically, we find that the post- vs. pre-event consensus difference is statistically indistinguishable from zero across all event windows in both columns 2 and 3.

Next, we examine how analysts' professional experiences with temperature shocks affect their responsiveness. In particular, we hypothesize that analysts who covered firms that experienced temperature shocks in the past would adjust their forecasts more quickly for firms that are currently experiencing extreme temperatures. For example, analysts who were professionally active during the widespread heat waves of the 1980s and 1990s might be more likely to understand and react to future extreme temperatures than younger analysts who had not experienced past events. This conjecture is motivated by the work of Malmendier and Nagel (2011, 2015), among others, who show that individuals' past experiences are a significant driver of their future economic expectations.

We test this conjecture two ways, at the firm and industry levels. At the firm level, we classify analysts as experienced with past temperature shocks if they have previously covered a firm that experienced an extreme temperature event during our sample. At the industry level, we expand this definition to include analysts that covered any firm in the same GICS industry during the quarter that a firm in the industry experienced a past extreme temperature event. In each case, we calculate separate mean consensus forecasts among experienced and non-experienced analysts. In columns 4 and 5 of Table C.1, we find no evidence that analysts who have previously covered a firm experiencing a temperature shock are more responsive to extreme temperature events. We find similar results when we expand the definition of experienced analysts to the industry level in columns 6 and 7.

Finally, we investigate how political views affect analysts' responsiveness to extreme weather events. We do this in two ways. First, we exploit geographic variation in climate change beliefs to understand whether these views affect the responsiveness of analyst estimates to extreme temperature events. Our conjecture is that analysts located in areas that are more receptive to scientific evidence of climate change will also respond to the potential impact of extreme temperature events more quickly. Second, given the link between political affiliations and views toward climate change (McCright and Dunlap, 2011), we expect that Democrat-leaning analysts' forecasts would be more responsive to extreme temperature events.

To implement these tests, we exploit the significant geographic variation of beliefs toward climate change documented and made available by Howe et al. (2015). Through the Yale Program on Climate Change Communication (YPCCC), the authors provide public climate change opinion estimates at the county level.[22] To understand whether local climate change opinions affect how quickly analysts react to extreme weather events, we combine the climate change opinion data with analyst locations. In Table C.1, columns 8 and 9, we then examine how post-event forecast revisions vary across analysts located in counties that are receptive to climate change versus those in locations that are opposed to the idea. We find no evidence that geographic variation in climate change beliefs affect analysts responsiveness to extreme temperature events.

As a more direct test of the effect of political views, we examine how analysts' post-event forecast revisions vary across Democrat vs. Republican analysts. We obtain data on analysts' political contributions to party-affiliated committees, as outlined by Hong and Kostovetsky (2012) and Jiang et al. (2016), in order to classify their political preferences. We then calculate Republican and Democrat consensus forecasts for the days surrounding a subset of extreme temperature events in our sample for which we have data on analysts' party affiliations. As with our previous tests, in columns 10 and 11 we neither find statistical evidence that either group of analysts exhibit a significant response to extreme temperature events, nor do we find evidence that one group of analysts is more responsive than the other.

C2. Stock price results

Next, we examine whether the prices of stocks headquartered in locations where investors believe in climate change adjust to extreme temperature events more quickly. This test draws on the literature documenting local bias and geographically proximate investors' role in the price formation of local stocks (e.g. Coval and Moskowitz, 2001; 2002; Hong et al., 2008). To implement the test, we once again draw on geographic estimates of climate change beliefs made available by the YPCCC. Specifically, we match these estimates with the headquarters location of each firm experiencing a temperature event in our sample. We then sort events into terciles based on the percentage of county residents who believe that climate change will harm people in the U.S.

In columns 2 and 3 of Table C.2, we respectively calculate our event study statistics for the top (i.e., Pro-CC) and bottom (i.e., Anti-CC) terciles of local views toward climate change (for comparison, column 1 presents the unconditional baseline estimate). While we find suggestive evidence that stocks headquartered in Pro-CC areas react in the correct direction (i.e., negative instead of positive, as for the Anti-CC group), the CARs for both groups across all event windows are statistically indistinguishable from zero.

[22] The specific measure we use is the percentage of county residents who believe that climate change will harm people in the U.S. The data are available at: http://climatecommunication.yale.edu/visualizations-data/ycom-us-2016/.

Table C.2
Cumulative abnormal returns surrounding extreme temperature events. This table reports estimates from stock price adjustment tests surrounding extreme temperature events. We define extreme temperature events as days on which firms are exposed to temperature extremes that would imply a statistically significant effect on firm profitability, given our industry-by-quarter earnings estimates. Heat (cold) shock events occur on days when the sales-weighted average maximum (minimum) temperature across a given firm's establishment locations rises above (falls below) the critical temperature thresholds summarized in Table 2. We allow for multiple events within a given firm-fiscal quarter, but require that event dates be at least 21 trading days apart so that our longest event windows do not overlap. For each of the extreme temperature events, we collect data on daily stock returns in the [−150,+20] day event time window relative to the temperature event date. We then estimate factor regressions using the Carhart (1997) 4-factor model for each firm-event over the 30 days from day −150 to day −121. Using the estimated factor coefficients, we calculate normal and abnormal returns over the period [−120,+20]. We multiply abnormal returns by negative one for temperature events associated with a positive effect on earnings. We calculate and report cumulative abnormal returns (CARs) over several event windows. In column 1, we consider all extreme temperature events in our sample. In columns 2 and 3, we respectively calculate our event study statistics for the top (i.e., Pro-CC) and bottom (i.e., Anti-CC) terciles of local views toward climate change. We match county-level estimates of climate change beliefs from the Yale Program on Climate Change Communication with the headquarters location of each firm experiencing a temperature event in our sample. We then sort events into terciles based on the percentage of county residents who believe that climate change will harm people in the U.S. t-statistics included in parentheses below coefficient estimates are calculated using standard errors adjusted for clustering across events within the same fiscal quarter.

		Local climate views	
Event window	All events (1)	Pro-CC (2)	Anti-CC (3)
[−120,+20]	0.003	−0.002	0.002
	(0.64)	(−0.33)	(0.30)
[−110,+10]	0.001	−0.001	0.003
	(0.43)	(−0.35)	(0.67)
[−15,+5]	0.001	−0.002	0.002
	(0.44)	(−0.86)	(0.75)
[−11,+1]	0.001	0.001	0.001
	(0.95)	(0.89)	(0.71)
N events	8,584	2,719	2,712

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2023.07.002.

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