Temperature Shocks and Earnings News*

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Abstract – Climate scientists project a rise in both average temperatures and the frequency of temperature extremes. We study how extreme temperatures affect companies' earnings. We combine granular daily data on temperatures across the continental U.S. with locations of public companies' establishments to build a panel of quarterly firm-level temperature exposures (1990-2015). Extreme temperatures significantly impact earnings in over 40% of industries. Some industries are harmed by temperature shocks while others benefit. Analysts and investors do not immediately react to observable intra-quarter temperature shocks, but earnings forecasts account for temperature effects by quarter-end in many, though not all, industries.

Keywords: Climate shocks, temperature extremes, earnings predictability, sell-side analysts, stock returns.

JEL Classification: G12, G14, Q54.

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1. Introduction

The body of scientific evidence supporting climate change and its anthropogenic causes is overwhelming. In particular, the Intergovernmental Panel on Climate Change (IPCC, 2014) reports a series of alarming facts. First, mean temperatures are rising. Temperatures in each of the previous three decades have been warmer than the last. Collectively, the 30-year period from 1983 to 2012 was likely the warmest in the Northern Hemisphere over the last 1,400 years. Second, extreme weather events are becoming more prevalent. On a global scale, the prevalence of cold and warm temperature extremes has increased. Further, climate scientists find that in some locations, the frequency of heat waves has more than doubled and is expected to increase by a factor of almost five over the next 50 years (Lau and Nath, 2012).

Despite the scientific evidence in support of climate change, little is known about how climate risks affect earnings and valuations in the U.S. corporate sector. This lack of evidence comes with potentially important consequences. For example, the U.S. recently decided to withdraw from the Paris Climate Agreement, citing the alleged harm to the American economy that would result from controlling carbon emissions. Key policy makers, on the other hand, assert that action on climate change could help American workers and the economy (e.g. Rubin, 2014; Stiglitz, 2017). At the same time, there is a diversity of political environments for climate policy among voters across the U.S. (Howe et al., 2015), and American business leaders have largely remained silent on climate change, despite extensive corporate lobbying on a wide array of other issues (e.g. Whitehouse, 2016; Gunther, 2017).

We aim to inform this debate by conducting the first study to provide direct evidence on how extreme temperature events affect companies' earnings and stock prices in the U.S. Specifically, we estimate the profitability effects of time-variation in quarterly temperature exposures at firms' establishment locations. We also examine whether key market participants, sell-side analysts and investors, understand the relationship between extreme temperatures and corporate profitability. There are several channels through which extreme

temperatures are likely to affect corporate profits.[1]

First, a growing literature establishes the link between extreme temperatures and agricultural outcomes. For example, Fisher et al. (2012) demonstrate the negative impact of temperature on crop yields. Furthermore, Schlenker and Roberts (2009) find sharply stronger effects when temperatures exceed crop-specific thresholds. These findings suggest a link between extreme temperatures and corporate earnings in agricultural and related industries.

Even outside of agriculture-related industries, there is a probable link between extreme temperatures and corporate profits. In particular, temperature extremes have been shown to impact labor productivity. Specifically, Graff-Zivin and Neidell (2014) study time use among U.S. workers and demonstrate that extremely hot temperatures reduce hours worked across several heat-sensitive industries.[2] Moreover, Jones and Olken (2010), Hsiang (2010), and Dell, Jones, and Olken (2012) find that temperature shocks negatively affect light manufacturing exports and reduce output in the industrial and service sectors. Despite this suggestive evidence, research providing direct evidence on the link between temperature exposure and corporate profitability is, to our knowledge, non-existent. One of our goals is to fill this gap by characterizing the temperature-profitability relationship for the full set of industries in the U.S. corporate sector (i.e., agricultural and non-agricultural industries).

We begin by building a detailed panel of U.S. firms' temperature exposures (i.e., time spent at different temperatures). We utilize a set of granular climate data that documents daily temperatures across 481,631 16-square-kilometer (i.e., 4×4km) grids covering the continental United States from 1981 to 2015. We obtain these data from the PRISM Climate Group, the U.S. Department of Agriculture's official climatological database.[3] We then com-

[1]Because changes in mean temperatures occur over long periods of time, estimating the effects associated with this channel of climate change is very difficult. Instead, using the latest approach in the climate impact literature (e.g. Schlenker and Roberts, 2009; Hsiang, Burke, and Miguel, 2013; Burke, Hsiang, and Miguel, 2015), we focus on the impact of exposure to extreme temperatures at the quarterly and intra-quarter frequencies. Temperature extremes are exogenous climate events that allow us to quantify the potential financial damages/benefits associated with climate change on companies' earnings in a concrete way.

[2]In addition to agriculture, these include: forestry, fishing, and hunting; mining; construction; manufacturing; and transportation and utilities.

[3]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.

bine the PRISM climate data with detailed data on U.S public firms' geographic footprints to generate measures of weather exposure over the course of firms' fiscal quarters. To capture firms' geographic footprints, we obtain establishment-level data from the NETS database. This database provides addresses for every U.S. establishment owned by each public firm 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?[4]

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.[5]

We show that hot and cold temperature extremes affect this diverse set of industries in

[4]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, Mérel, and Ortiz-Bobea, 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.

[5]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 Sections 3. and 4.1. for further details on these tests.

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.

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 change in earnings, on average. 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 they propose

as having high climate exposure due to heat-induced labor productivity losses.

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 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. Specifically, Hong, Li, and Xu (2017) use an international drought severity index to demonstrate that food stocks fail to efficiently discount the risks of droughts, generating predictable patterns in returns. In contrast, Bansal, Kiku, and Ochoa (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 ma-

chinery), 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.

Next, we examine how geographic differences in views toward climate change affect analysts' and investors' responsiveness to extreme temperature events. Survey studies have found that more than a third of Americans do not believe climate change is happening and that there is significant variation in climate change beliefs. For example, Howe et al. (2015) find that in some counties, up to 80% of residents do not believe that the effects of climate change will harm Americans. Using new publicly available data from the Yale Program on Climate Change Communication, we examine whether local views on climate change affect the responsiveness of analyst estimates and stock prices to extreme weather events. Our conjecture is that analysts and investors 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. Furthermore, given recent evidence that attitudes toward the existence and effects of climate change are highly correlated with political affiliations (McCright and Dunlap, 2011), we also hypothesize that Democrat-leaning analysts may be more responsive to extreme temperatures than their Republican counterparts. We test this hypothesis using data on analysts' political contributions to party-affiliated committees (Hong and Kostovetsky, 2012; Jiang, Kumar, and Law, 2016). We find that analysts and investors are generally slow to respond to extreme temperature events, regardless of political affiliations and local views on climate change.

Finally, we study whether analysts located in areas that are affected by temperature shocks are more responsive in updating their earnings forecasts for firms with local establishments. Similarly, we examine how analysts' past experiences with temperature shocks affect their responsiveness to current shocks. Motivated by the body of literature showing that individuals' past experiences are a significant driver of their future economic expectations (e.g. Malmendier and Nagel, 2011, 2015), we hypothesize that analysts who have previously experienced temperature shocks (e.g., severe heat waves) 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 would be more likely to understand and react to future extreme temperatures than younger analysts who had not experienced these events. However, we find no evidence that either group of analysts exhibits a significant response to extreme temperature events.

Our paper makes several contributions to the literature. First, our study contributes to the body of research in science and economics documenting the effects of extreme weather events and climate shocks on various outcomes. For example, studies show that the negative impacts of extreme temperatures extend to labor supply (Graff-Zivin and Neidell, 2012, 2014), crop yields (Schlenker and Roberts, 2009; Fisher et al., 2012), light manufacturing exports and output in the industrial and service sectors (Hsiang, 2010; Jones and Olken, 2010; Dell, Jones, and Olken, 2012), and even crime and human mortality (Hsiang et al., 2017). Only a few papers assess the effects of climate shocks in financial markets (Bansal, Kiku, and Ochoa, 2016a,b; Hong, Li, and Xu, 2017). We contribute to this literature by documenting how one aspect of climate change (i.e., increased prevalence of temperature extremes) affects companies' earnings in the U.S.

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, Kramer, and Levi (2003) document that investors are more risk averse during winter months with fewer daylight hours. Bassi, Colacito, and Fulghieri (2013) confirm this finding in an experimental setting, showing that sunshine and good weather promote risk taking. Goetzmann, Kim, Kumar, and Wang (2014) demonstrate that cloudy days impact institutional investors' assessment of mispricing and influence their trading decisions. DeHaan, Madsen, and Piotroski (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. 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 our approach allows us to further establish and understand the real economic effects of weather and climate.

Finally, our study contributes to a growing literature that focuses on how political values impact financial market outcomes, including institutional investors' portfolio allocations (Hong and Kostovetsky, 2012), individual investors' stock participation decisions (Bonaparte, Kumar, and Page, 2017), and companies' corporate social responsibility practices (Di Giuli and Kostovetsky, 2014). Our paper adds to this literature by examining how political values affect the responsiveness of stock prices and analysts' earnings estimates to intra-quarter extreme temperature events. Recent surveys show that public attitudes toward the existence and effects of climate change are driven to a large extent by political affiliations (McCright and Dunlap, 2011; Howe et al., 2015). Rational investors and analysts should not let attitudes toward climate change affect their ability to assess the cash flow effects of temperature extremes. Our setting allows us to observe whether climate change attitudes inspired by political beliefs affect the ability of analysts and investors to process observable earnings news captured by temperature shocks.

2. Methodology and research design

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, Jones, and Olken (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.[6] 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 climate sensitivity.

Next, we aim to understand how quickly analysts and investors respond to intra-quarter

[6]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.

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, Li, and Xu (2017) show that food stocks 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, Kiku, and Ochoa (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:

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.

To the extent that stock prices and earnings forecasts do not fully reflect extreme temperatures, we would like to understand how geographic variation in analysts' locations affects the responsiveness of their earnings estimates and stock prices to extreme weather events. Using analyst location data, as previously collected by Malloy (2005), our conjecture is that analysts who have themselves experienced temperature shocks will be more responsive to current shocks. This is motivated by the work of Malmendier and Nagel (2011, 2015), among others, demonstrating that individuals' formative experiences are a significant driver of their expectations, leading to the following hypotheses:

Hypothesis 3a: Among firms in industries with temperature-sensitive earnings, the speed of adjustment of earnings forecasts following intra-quarter exposure to extreme temperatures will be faster among analysts located in areas that are affected by the temperature shocks.

and

Hypothesis 3b: Among firms in industries with temperature-sensitive earnings, the speed of

adjustment of earnings forecasts following intra-quarter exposure to extreme temperatures will be faster among analysts who have previously experienced severe heat waves.

We also examine how local beliefs surrounding climate change affect analysts' responsiveness to temperature-related earnings news. Survey studies have found that more than a third of Americans do not believe climate change is happening, and that there is significant variation in climate change beliefs. For example, Howe et al. (2015) find that in some counties up to 80% of residents do not believe that the effects of climate change will harm Americans. Recent surveys show that public attitudes toward the existence and effects of climate change are driven to a large extent by political affiliations (McCright and Dunlap, 2011; Howe et al., 2015).

Our conjecture is that analysts located in areas that are more receptive to scientific evidence of climate change may respond to the potential impact of extreme temperature events more quickly. Further, given the link between political affiliations and attitudes toward climate change, we expect that Democrat-leaning analysts may be more responsive to extreme temperatures. Finally, drawing on previous literature documenting local bias and local investors' role in the price formation of local stocks (e.g. Coval and Moskowitz, 2001, 2002; Hong, Kubik, and Stein, 2008), we also expect prices of stocks headquartered in areas where residents believe in the harmful effects of climate change to adjust to extreme weather more quickly. Overall, these conjectures lead to our final set of hypotheses:

Hypothesis 4a: Among firms in industries with temperature-sensitive earnings, the speed of adjustment of earnings forecasts following intra-quarter exposure to extreme temperatures will be faster among Democrat-leaning analysts.

and

Hypothesis 4b: Among firms in industries with temperature-sensitive earnings, the speed of adjustment of earnings forecasts following intra-quarter exposure to extreme temperatures will be faster among analysts located in areas that are more receptive to scientific evidence of climate change.

and

Hypothesis 4c: Among firms in industries with temperature-sensitive earnings, the speed of adjustment of stock prices following intra-quarter exposure to extreme temperatures will be faster for firms headquartered in areas where residents are more receptive to scientific evidence of climate change.

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

2.2. 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. 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-level subsamples. In particular, we use the 68 Global Industry Classification Standard (GICS) six-digit industry classifications to construct subsamples for modeling this relationship. This choice is guided by the evidence of Bhojraj, Lee, and Oler (2003), who show that among various industry classification schemes, GICS classifications are better at capturing common cross-sectional firm characteristics and comovement in stock returns.

Second, because weather is location-specific, it is important to account for firms' geographic footprints. To do so, we obtain establishment-level data from the National Establishment Time Series (NETS) database. This database provides addresses for every U.S.

establishment owned by each public firm over the period from 1990 to 2015. In addition to locations, the database provides information on the portion of a firm's annual sales generated at each of its establishments, as well as information on the number of employees working at each location. We provide further details on the NETS database in Section 3.

We use the firm-establishment location data to construct a quarterly firm-level temperature exposure variable that measures the time spent at different temperature levels.[7] We then use this measure to test whether exposure to extreme temperatures affects firm profitability over a fiscal quarter. Furthermore, we examine how stock prices and analysts' earnings forecasts respond to firms' extreme temperature exposures. Importantly, we account for potential non-linear effects of temperature exposure by estimating third-order polynomials in measuring the relationship between temperature exposure and our financial market outcomes of interest. This methodology, which we detail next, is state-of-the-art in the climate impact literature (e.g. Schlenker and Roberts, 2009; Blanc and Schlenker, 2017).

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. We assume that firm-level earnings depend on temperature, denoted by h, across a firm's establishments. Following the climate impact literature closely (e.g. Schlenker and Roberts, 2009; Blanc and Schlenker, 2017), we further assume that temperature effects are time-separable and potentially non-linear within quarters.[8]

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

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

[7]Using location-specific measures of exposure to varying temperature levels allows us to accurately capture firm-level exposure to temperature extremes. Importantly, the alternative approach of averaging temperatures (even maximum temperatures) over distant locations would conceal the exposure to extreme levels.

[8]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.

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).[9]

Empirically estimating the process in equation 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 k-th order Chebyshev polynomial.[10]

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

[9]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, Glaeser, and Kerr, 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.

[10]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.

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.

3. Data description

In order to examine the relationships between temperature exposure, firm profitability, and financial market expectations, we combine data from several sources.

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. Figure 1 presents an example of the grids for Tompkins County, NY.

To compute the exposure to 1°C temperature bins varying from -15 to 50°C, we closely follow 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.[11] Figure 2 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

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

mean number of hours spent above 30°C in July.[12]

To capture firms' geographic footprints, we obtain establishment-level data from the NETS Publicly Listed Database produced by Wall & Associates. This database provides addresses for every U.S. establishment owned by each 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 generated at each of its establishments, as well information on the number of employees working at each location. This allows us to track the economic importance of a firm's establishments over time.[13] Figure 3 displays the establishment locations owned by all publicly traded U.S. firms in our sample during the sample period. Figure 4 plots these locations for firms within each of the 10 GICS sectors.

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.[14]

[12]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.

[13]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.

[14]As a robustness check, we verify our results using different weighting schemes, including weights based on number of employees and equal weights.

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 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. 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.

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.

4. Empirical tests and results

4.1. 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 equation 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 Figure 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 Figure 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

[15]We plot the full set of earnings response functions for each of 59 GICS six-digit industries over all calendar quarters (Q1-Q4) in Appendix Figure A1. We also report all corresponding regression coefficients and associated test statistics in Appendix Table A2. In the remainder of our analysis, we continue to focus on the set of industry-quarter combinations that have significant earnings sensitivity to extreme temperatures.

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 A1, 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.

4.1.1 Robustness tests: Foreign operations, hedging, and adaptations

There are several important caveats to note with respect to the temperature effects we document. First, a 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' 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 Appendix Table A2 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

[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.

the extreme 5% right (left) tail of the temperature 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.

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 Appendix Table A2). 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 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.

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 Appendix Table A2). 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 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.

4.1.2 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

each other. For example, an industry that exhibits a positive relation between 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 Figure 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 Figure 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.

In a separate set of tests, we collect additional data related to the heating/cooling channel. In particular, 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 mod-

est, 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).

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.[17] 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.[18]

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

[17]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.

[18]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.

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.

4.1.3 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 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 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, Hoffmann, and Phan (2018) 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.

Given our initial evidence that extreme weather can help to predict earnings 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.

4.2. Do analysts understand the impact of extreme temperature?

Sell-side analysts are charged with formulating earnings forecasts. 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 equation 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 equation 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.

Figure 8 shows the analyst consensus forecast estimates for the 24 industries (32 industry-quarters) in our sample where temperature extremes affect earnings. Table 5 shows the reported earnings (E), analyst consensus forecast estimates (F), and earnings surprises (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 5 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 the two industries with positive earnings shocks (leisure products and life science tools).

4.3. 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 respon-

siveness 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 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.

4.3.1 Analyst forecast results

The results of our earnings forecast event study tests are tabulated in Table 6. 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 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.

In column 1, we consider all analyst forecasts surrounding 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 9 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 6, 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.

In columns 2 and 3 of Table 6, we examine how analysts' locations affect their responsiveness to extreme temperature events. Our conjecture is that analysts who are located in areas affected by temperature shocks may be more likely to update their forecasts for firms with local operations (*Hypothesis 3a*). 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 (*Hypothesis 3b*). 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 6, 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 (*Hypotheses 4b* and *c*). 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 (*Hypothesis 4a*).

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.[19] To understand whether local climate change opinions affect how quickly analysts react to extreme weather events, we combine the climate

[19]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/.

change opinion data with analyst locations. In Table 6, 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, Kumar, and Law (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.

4.3.2 Stock price results

The estimates from our stock price adjustment tests are presented in Table 7. 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]).

In column 1 of Table 7, 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 Figure 10, Panel A, 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.

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, Kubik, and Stein, 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, 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. 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. Moreover, in Figure 10, Panel B, we find that the negative effect among the Pro-CC group of stocks (dashed line) is concentrated in the days leading up to the event date and that CARs for both groups are similar following extreme temperature days.

Taken together, our event study results suggest that analysts and investors are generally not responsive to extreme temperature events. However, in light of our results in the previous section, that analysts anticipate earnings shocks in many industries by quarter-end, it is likely that analysts learn about the effects of temperature shocks on firm profitability 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).

5. 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.

References

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016a, Climate change and growth risks, NBER Working Paper No. 23009.

——— , 2016b, Price of long-run temperature shifts in capital markets, NBER Working Paper No. 22529.

Bassi, Anna, Riccardo Colacito, and Paolo Fulghieri, 2013, 'O sole mio: An experimental analysis of weather and risk attitudes in financial decisions, *Review of Financial Studies* 26, 1824–1852.

Bhojraj, Sanjeev, Charles Lee, and Derek K Oler, 2003, What's my line? A comparison of industry classification schemes for capital market research, *Journal of Accounting Research* 41, 745–774.

Blanc, Elodie, and Wolfram Schlenker, 2017, The use of panel models in assessments of climate impacts on agriculture, *Review of Environmental Economics and Policy* 11, 258–279.

Bonaparte, Yosef, Alok Kumar, and Jeremy K Page, 2017, Political climate, optimism, and investment decisions, *Journal of Financial Markets (forthcoming)*.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel, 2015, Global non-linear effect of temperature on economic production, *Nature* 527, 235–239.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Colacito, Ricardo, Bridget Hoffmann, and Toan Phan, 2018, Temperatures and growth: A panel analysis of the united states, *Working paper, University of North Carolina*.

Coval, Joshua D., and Tobias J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

——— , 2002, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

DeHaan, Ed, Joshua Madsen, and Joseph D Piotroski, 2017, Do weather-induced moods affect the processing of earnings news?, *Journal of Accounting Research* 55, 509–550.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken, 2012, Temperature shocks and economic growth: Evidence from the last half century, *American Economic Journal: Macroeconomics* 4, 66–95.

Di Giuli, Alberta, and Leonard Kostovetsky, 2014, Are red or blue companies more likely to go green? Politics and corporate social responsibility, *Journal of Financial Economics* 111, 158–180.

Ellison, Glenn, and Edward L Glaeser, 1997, Geographic concentration in us manufacturing industries: A dartboard approach, *Journal of Political Economy* 105, 889–927.

——— , and William R Kerr, 2010, What causes industry agglomeration? evidence from coagglomeration patterns, *American Economic Review* 100, 1195–1213.

Fisher, Anthony C, et al., 2012, The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment, *American Economic Review* 102, 3749–3760.

Gammans, Matthew, Pierre Mérel, and Ariel Ortiz-Bobea, 2017, Negative impacts of climate change on cereal yields: Statistical evidence from France, *Environmental Research Letters* 12, 054007.

Goetzmann, William N, Dasol Kim, Alok Kumar, and Qin Wang, 2014, Weather-induced mood, institutional investors, and stock returns, *Review of Financial Studies* 28, 73–111.

Graff-Zivin, Joshua, and Matthew Neidell, 2012, The impact of pollution on worker productivity, *American Economic Review* 102, 3652–3673.

——— , 2014, Temperature and the allocation of time: Implications for climate change, *Journal of Labor Economics* 32, 1–26.

Gunther, Marc, 2017, Why won't American business push for action on climate?, *Yale Environment 360* [Online; posted 16-February-2017; http://e360.yale.edu/features/why-wont-american-business-push-for-action-on-climate].

Hirshleifer, David, and Tyler Shumway, 2003, Good day sunshine: Stock returns and the weather, *Journal of Finance* 58, 1009–1032.

Hong, Harrison, and Leonard Kostovetsky, 2012, Red and blue investing: Values and finance, *Journal of Financial Economics* 103, 1–19.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2008, The only game in town: Stock-price consequences of local bias, *Journal of Financial Economics* 90, 20–37.

Hong, Harrison G, Frank Weikai Li, and Jiangmin Xu, 2017, Climate risks and market efficiency, *Journal of Econometrics (forthcoming)*.

Howe, Peter D, et al., 2015, Geographic variation in opinions on climate change at state and local scales in the USA, *Nature Climate Change* 5, 596–603.

Hsiang, Solomon, et al., 2017, Estimating economic damage from climate change in the United States, *Science* 356, 1362–1369.

Hsiang, Solomon M, 2010, Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America, *Proceedings of the National Academy of sciences* 107, 15367–15372.

——— , Marshall Burke, and Edward Miguel, 2013, Quantifying the influence of climate on human conflict, *Science* 341, 1235367.

Huntington, Ellsworth, 1915, *Climate and civilization* (Harper & Bros.).

IPCC, 2014, Climate change 2014: Synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change, .

Jiang, Danling, Alok Kumar, and Kelvin KF Law, 2016, Political contributions and analyst behavior, *Review of Accounting Studies* 21, 37–88.

Jones, Benjamin F, and Benjamin A Olken, 2010, Climate shocks and exports, *American Economic Review* 100, 454–459.

Kamstra, Mark J, Lisa A Kramer, and Maurice D Levi, 2003, Winter blues: A SAD stock market cycle, *American Economic Review* 93, 324–343.

Kasznik, Ron, and Baruch Lev, 1995, To warn or not to warn: Management disclosures in the face of an earnings surprise, *The Accounting Review* pp. 113–134.

Lau, Ngar-Cheung, and Mary Jo Nath, 2012, A model study of heat waves over North America: Meteorological aspects and projections for the twenty-first century, *Journal of Climate* 25, 4761–4784.

Lev, Baruch, and Stephen H Penman, 1990, Voluntary forecast disclosure, nondisclosure, and stock prices, *Journal of Accounting Research* pp. 49–76.

Livnat, Joshua, and Richard R Mendenhall, 2006, Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts, *Journal of Accounting Research* 44, 177–205.

Malloy, Christopher J, 2005, The geography of equity analysis, *Journal of Finance* 60, 719–755.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

——— , 2015, Learning from inflation experiences, *Quarterly Journal of Economics* 131, 53–87.

McCright, Aaron M, and Riley E Dunlap, 2011, The politicization of climate change and polarization in the American public's views of global warming, 2001–2010, *Sociological Quarterly* 52, 155–194.

Purnanandam, Amiyatosh, and Daniel Weagley, 2016, Can markets discipline government agencies? Evidence from the weather derivatives market, *Journal of Finance* 71, 303–334.

Rubin, Robert E., 2014, How ignoring climate change could sink the U.S. economy, *The Washington Post* [Online; posted 24-July-2014; https://www.washingtonpost.com/opinions/robert-rubin-how-ignoring-climate-change-could-sink-the-us-economy/2014/07/24/].

Saunders, Edward M, 1993, Stock prices and wall street weather, *American Economic Review* 83, 1337–1345.

Schlenker, Wolfram, and Michael J Roberts, 2009, Nonlinear temperature effects indicate severe damages to US crop yields under climate change, *Proceedings of the National Academy of Sciences* 106, 15594–15598.

Skinner, Douglas J, 1994, Why firms voluntarily disclose bad news, *Journal of Accounting Research* 32, 38–60.

Starr-McCluer, Martha, 2000, The effects of weather on retail sales, Working Paper, Federal Reserve Board.

Stiglitz, Joseph E., 2017, Opinion: Protecting the planet is good for American workers, *MarketWatch* [Online; posted 6-June-2017; http://www.marketwatch.com/story/protecting-the-planet-is-good-for-american-workers-2017-07-03].

Till, Hilary, 2015, Why haven't weather derivatives been more successful as futures contracts? A case study, *Journal of Governance and Regulation* 4, 367–371.

Whitehouse, Sheldon, 2016, The climate movement needs more corporate lobbyists, *Harvard*

Business Review [Online; posted 25-February-2016; https://hbr.org/2016/02/the-climate-movement-needs-more-corporate-lobbyists].

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.

Table 1 (Continued)

	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

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 equation 2, with coefficients reported in Appendix Table A2 and associated earnings response functions displayed in Figure 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. & Distributors (+,27°) Commercial 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°)	Metals & Mining (+,28°) Machinery (-,28°) Airlines (+,24°) Capital Markets (+,25°)

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 equation 2, with revenues and operating costs as the dependent variables and associated response functions displayed in Figure 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-*)	Metals & Mining (E+,R+,C0) Machinery (E-,R-,C-) Airlines (E+,R+,C+) Capital Markets (E+,R+,C+)

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 equation 2, with cost of goods sold and SG&A expenses as the dependent variables and associated response functions displayed in Figure 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)	Metals & Mining (C0,COGS0,SGA0) Machinery (C-,COGS-,SGA-*) Airlines (C+,COGS+,SGA0) Capital Markets (C+,COGS+,SGA0)

Table 5

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 equation 2, with earnings forecasts and earnings surprises as the dependent variables and associated response functions displayed in Figure 8. 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)	Metals & Mining (E+,F+*,S+) Machinery (E-,F-,S-*) Airlines (E+,F+*,S0) Capital Markets (E+,F+*,S0)

Table 6

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	Yes	No	Yes	No	Yes	No	Anti-CC	Pro-CC	Republican	Democrat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
[-20,+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)
[-10,+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)
[-5,+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)
[-1,+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

Table 7

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 [-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. 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	Pro-CC	Anti-CC
	(1)	(2)	(3)
[-20,+20]	0.003	-0.002	0.002
	(0.64)	(-0.33)	(0.30)
[-10,+10]	0.001	-0.001	0.003
	(0.43)	(-0.35)	(0.67)
[-5,+5]	0.001	-0.002	0.002
	(0.44)	(-0.86)	(0.75)
[-1,+1]	0.001	0.001	0.001
	(0.95)	(0.89)	(0.71)
N events	8,584	2,719	2,712

Figure 1

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.

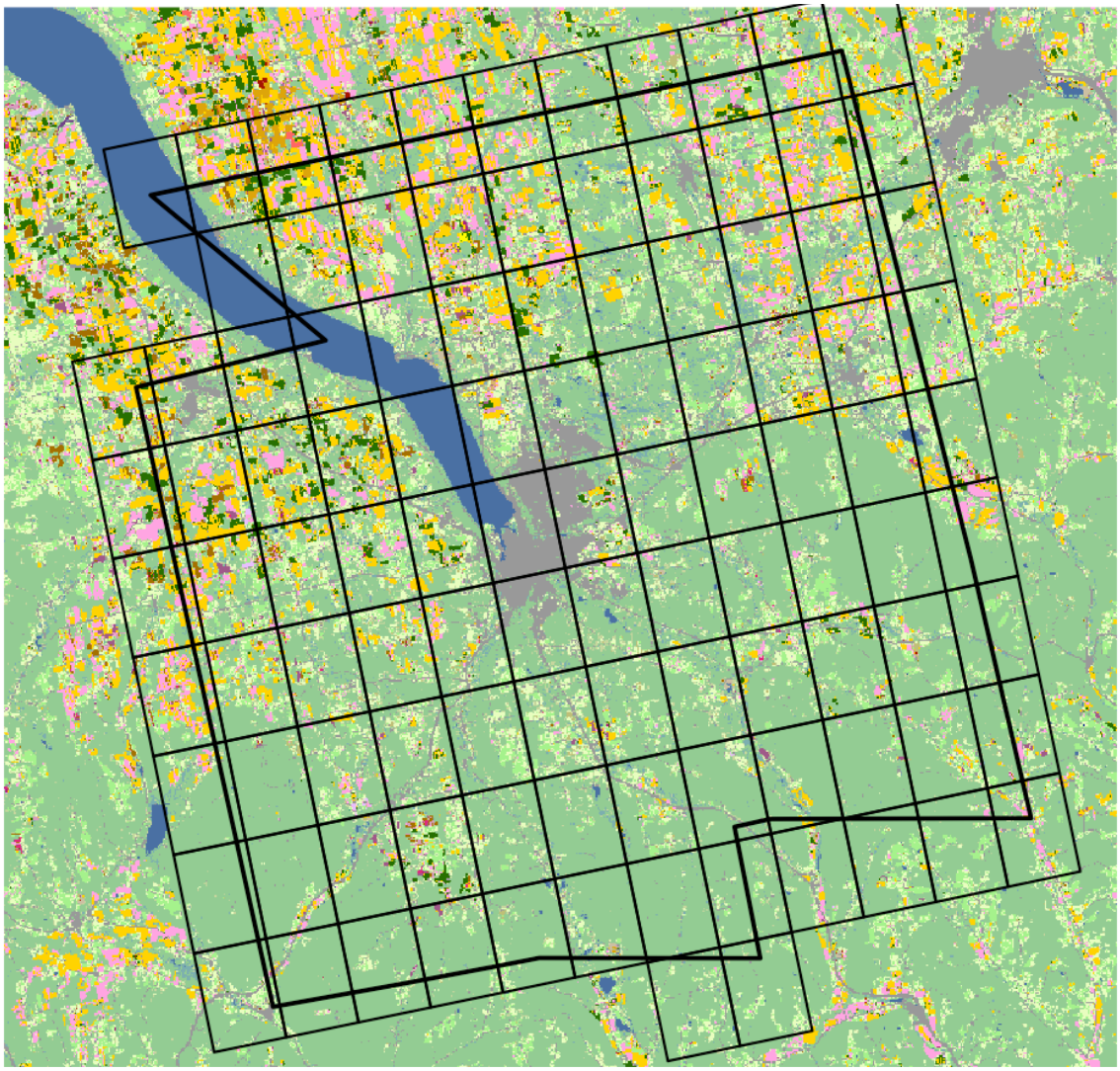


Figure 2

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.

Panel A: Exposure to Temperatures Above 30°C (hours), July 1999

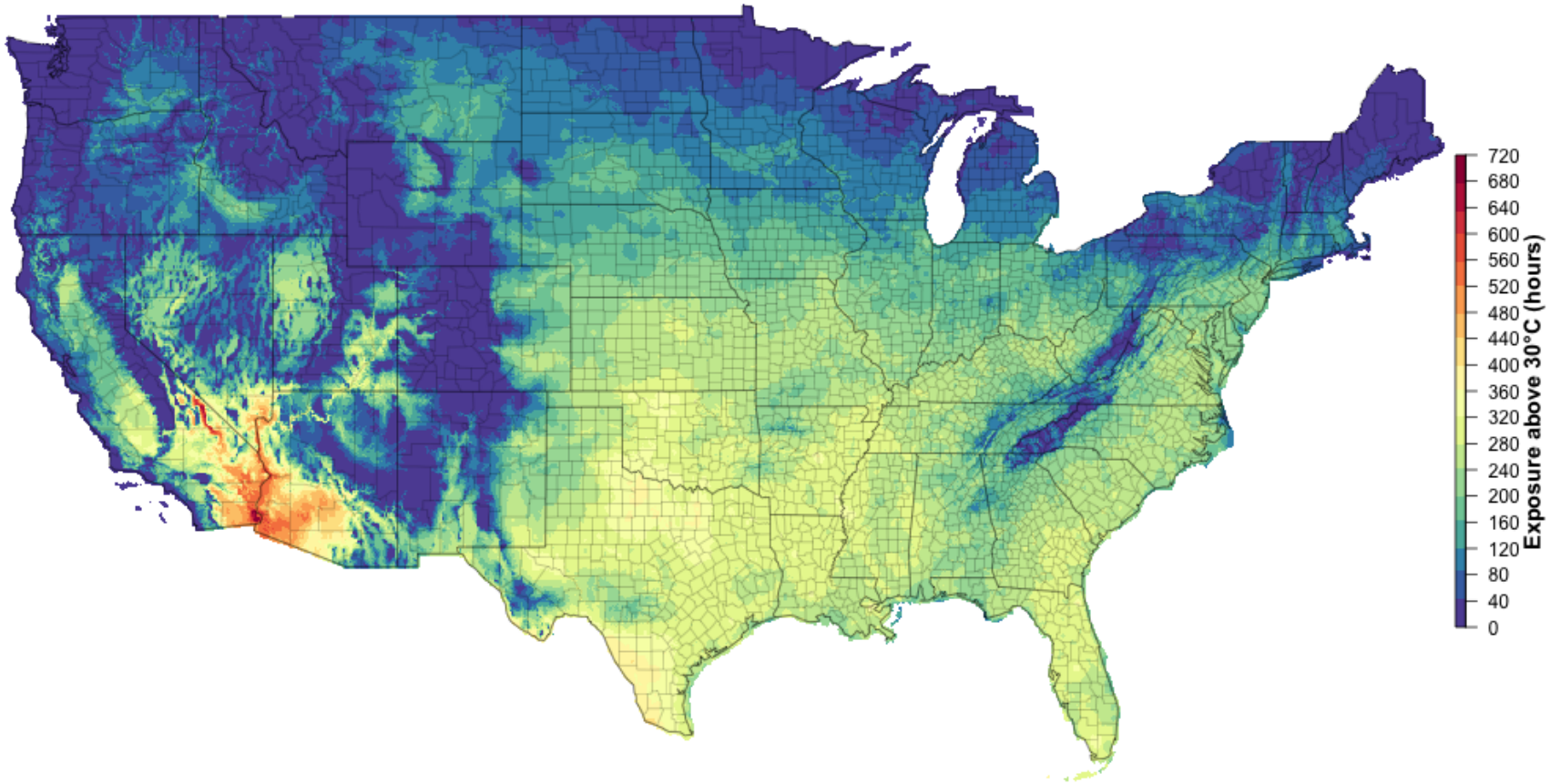


Figure 2 (Continued)

Panel B: Deviation in Exposure to Temperatures Above 30°C (hours relative to historical mean), July 1999

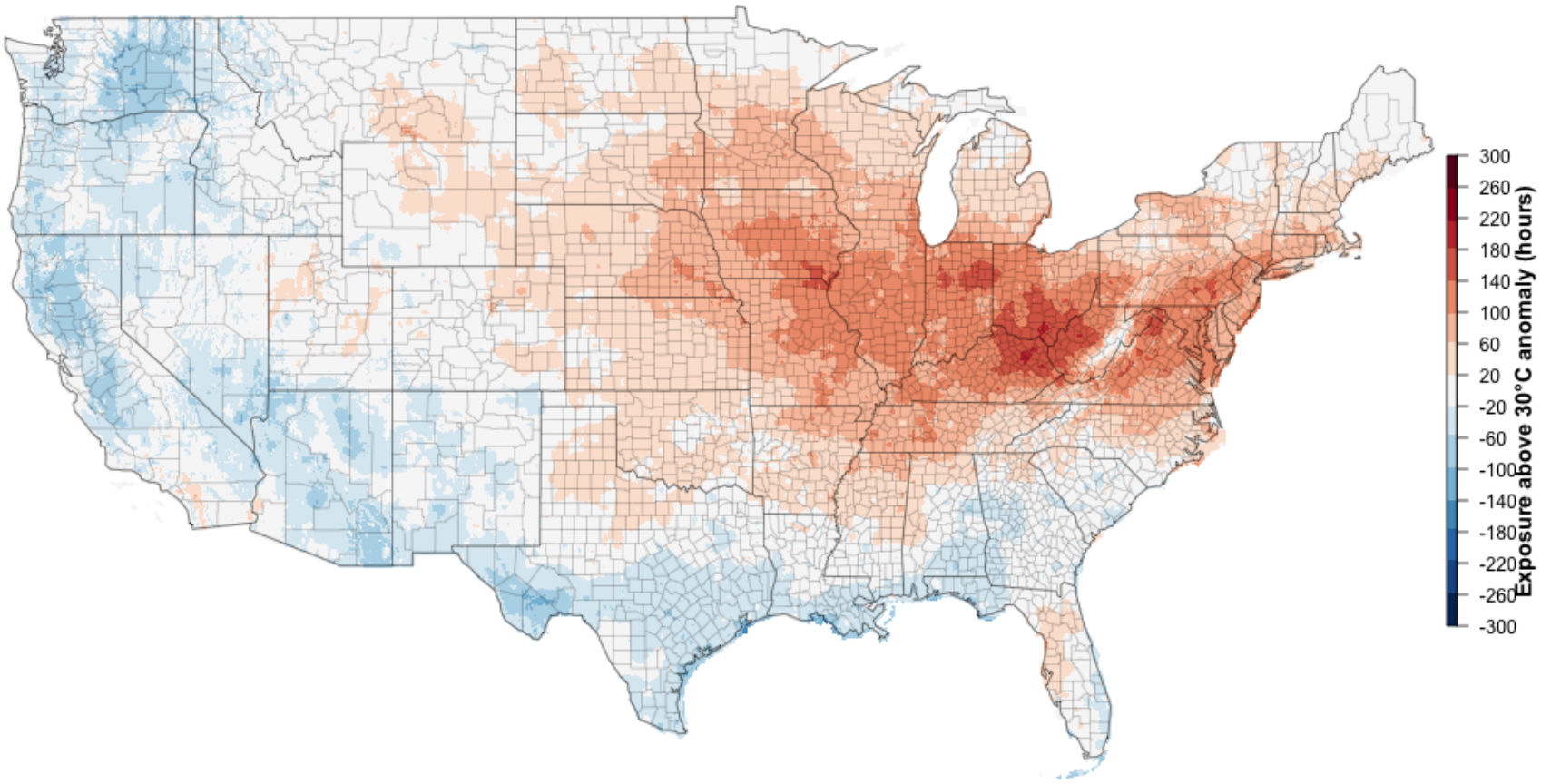


Figure 3

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.

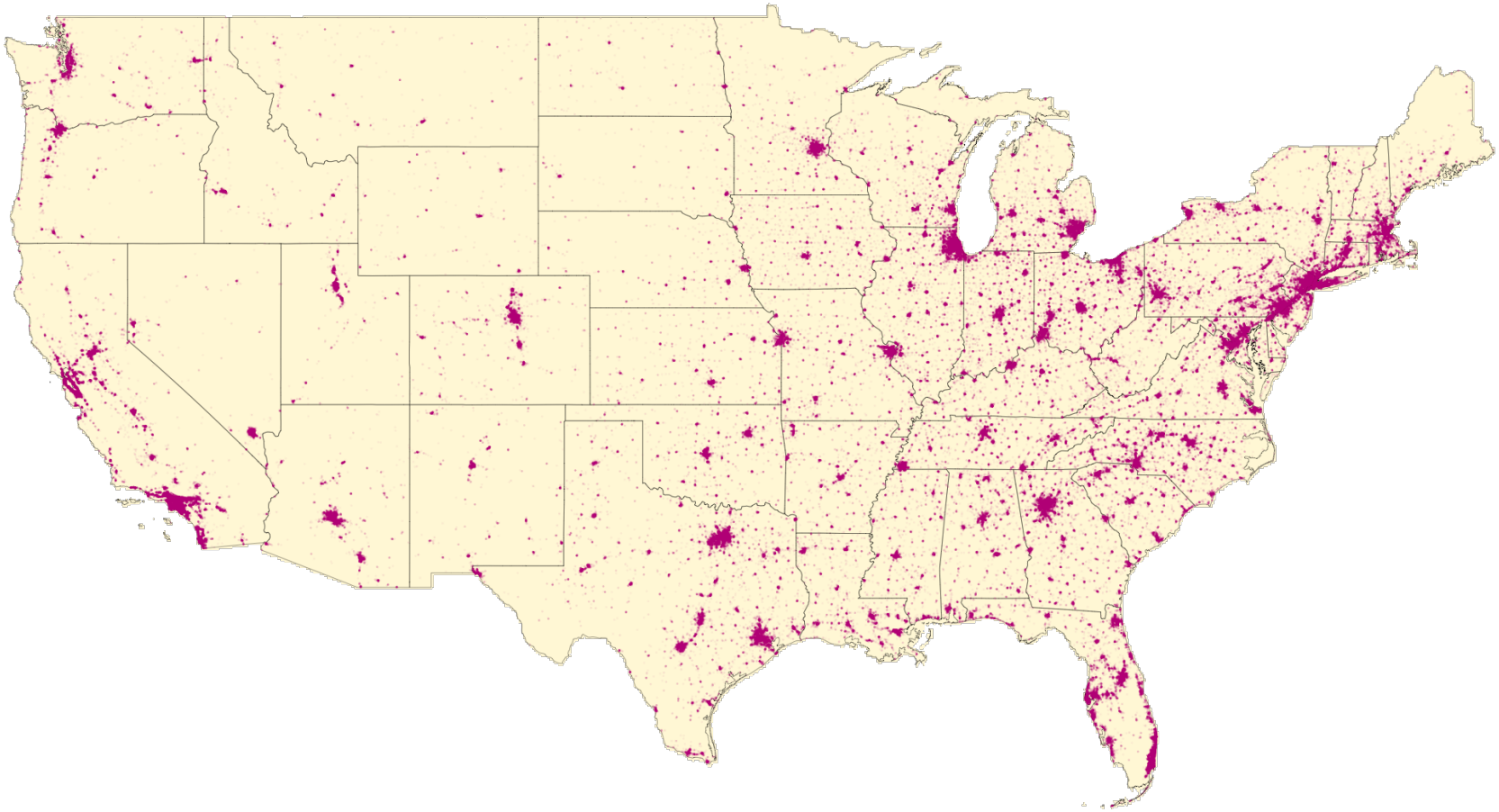


Figure 4

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.

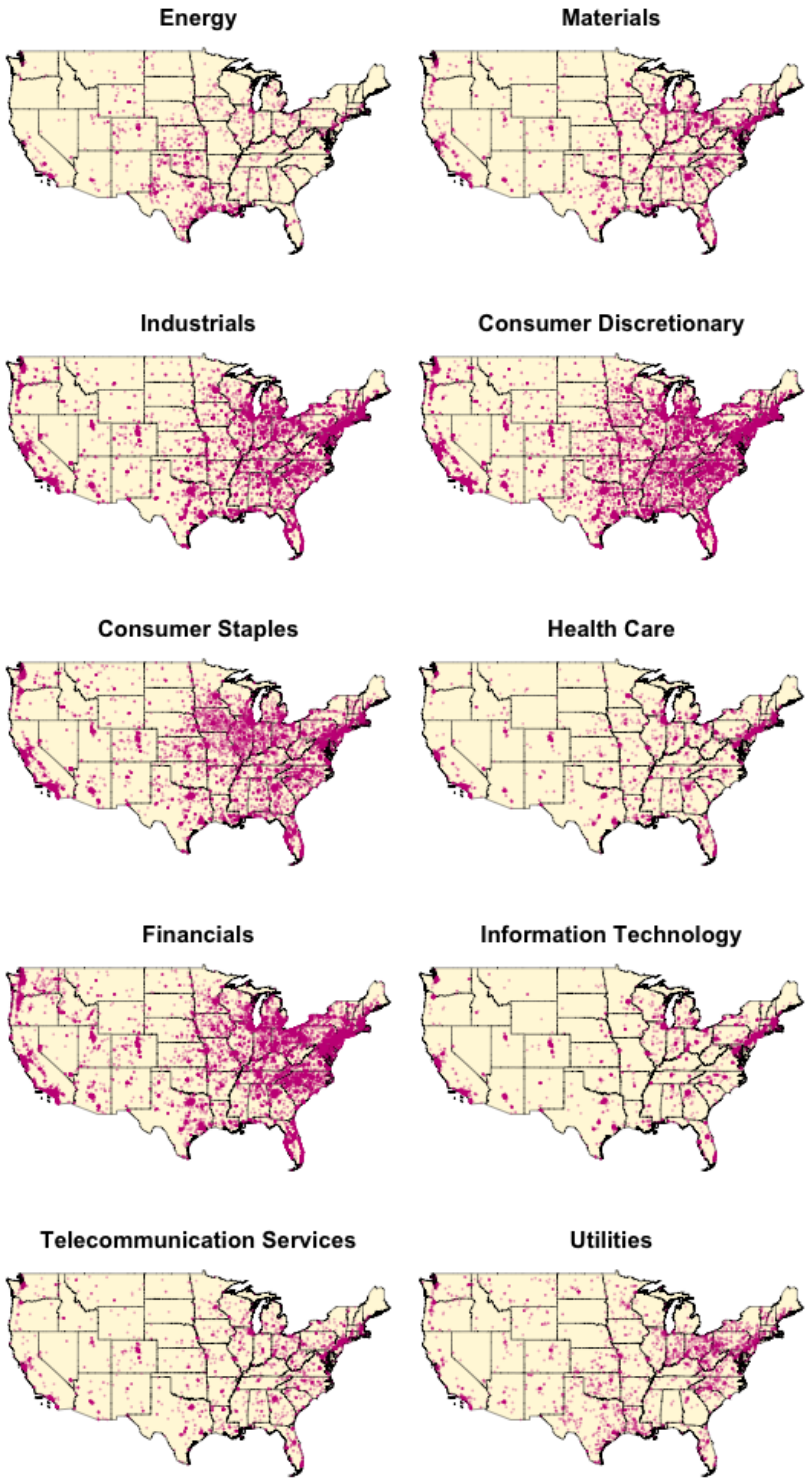
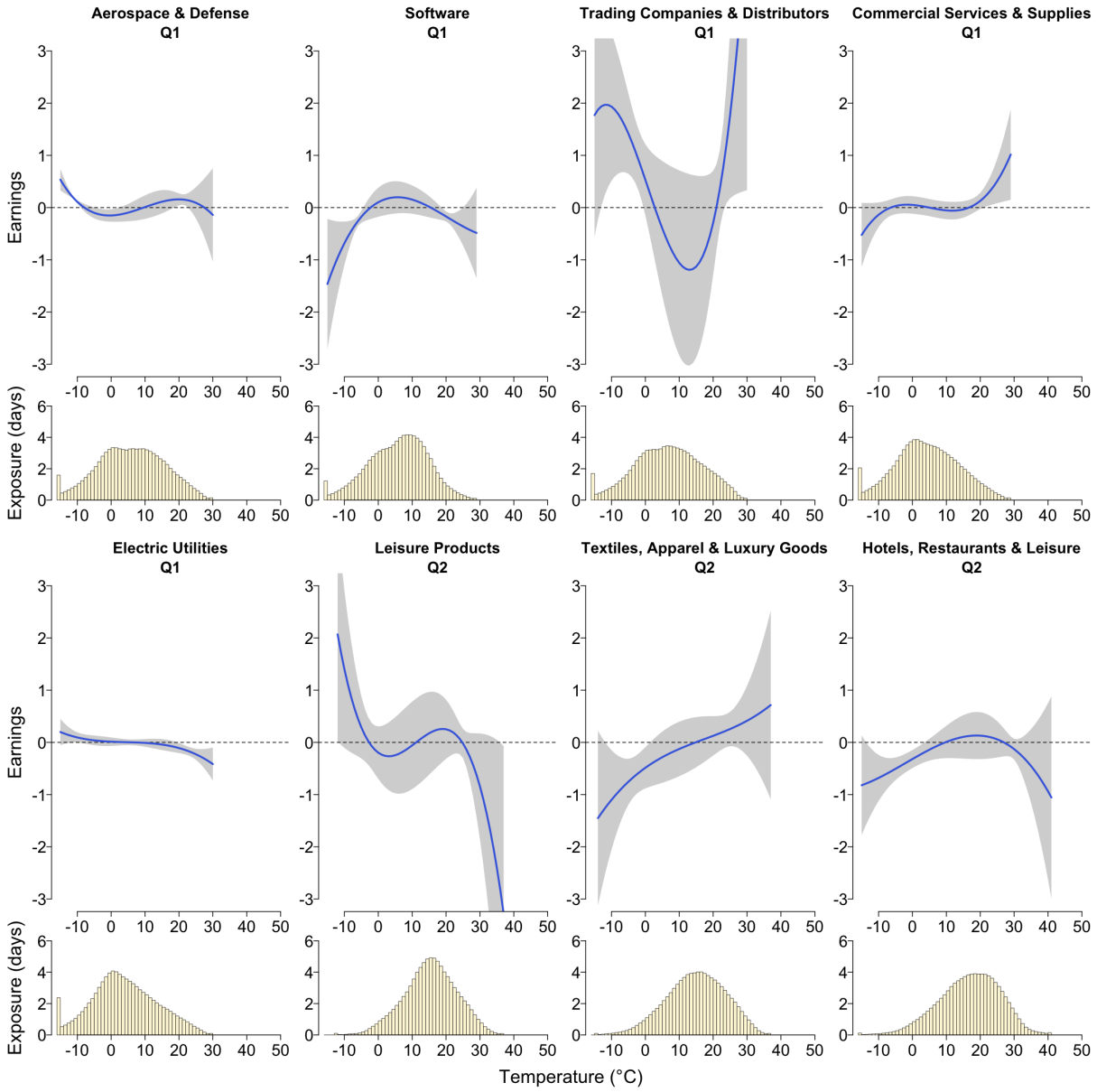


Figure 5

Nonlinear Relations Between Firm Profitability and Temperature

The figure displays the nonlinear effects of temperature exposure on profitability based on regression specifications (equation 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 Appendix Table A2. 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.



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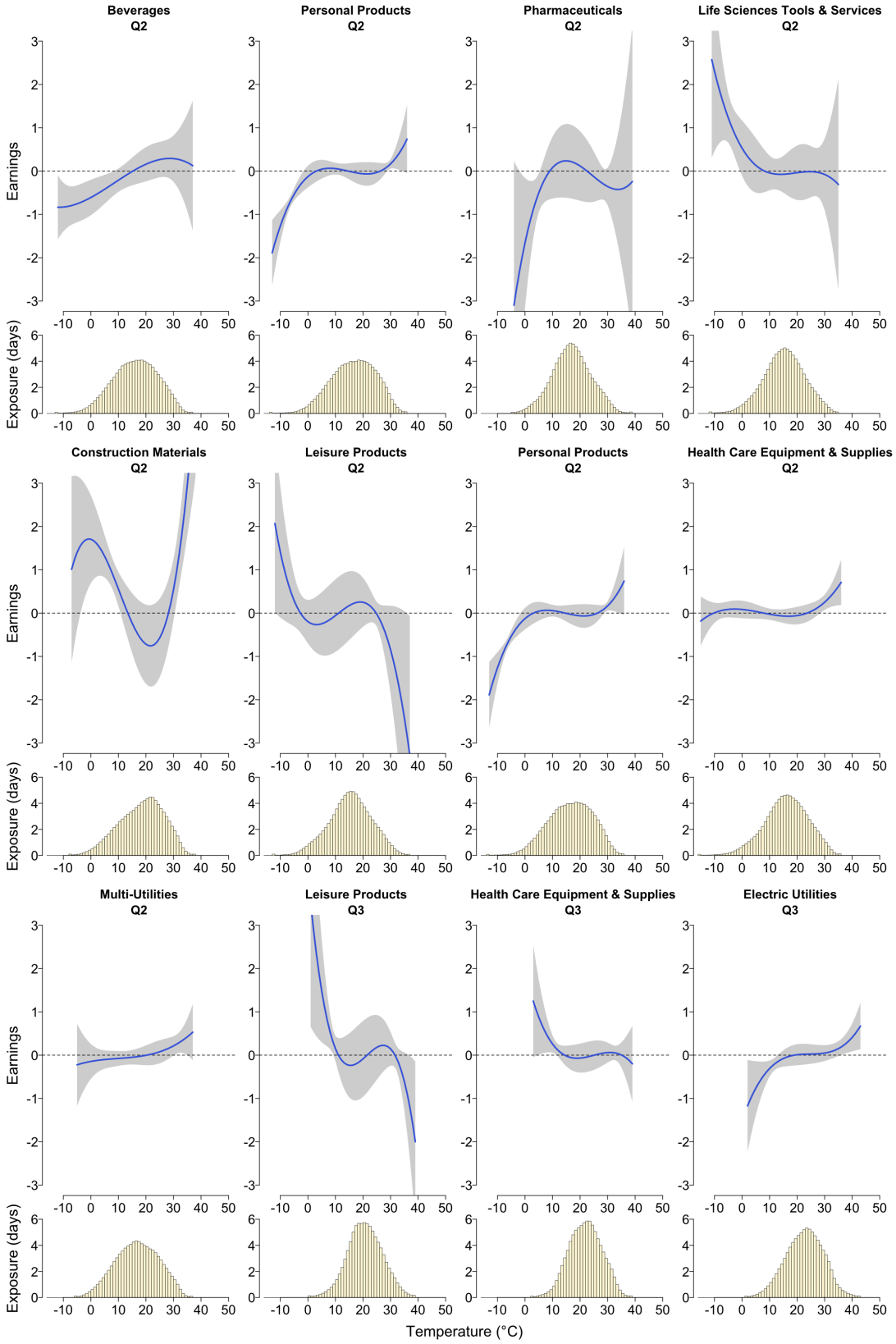

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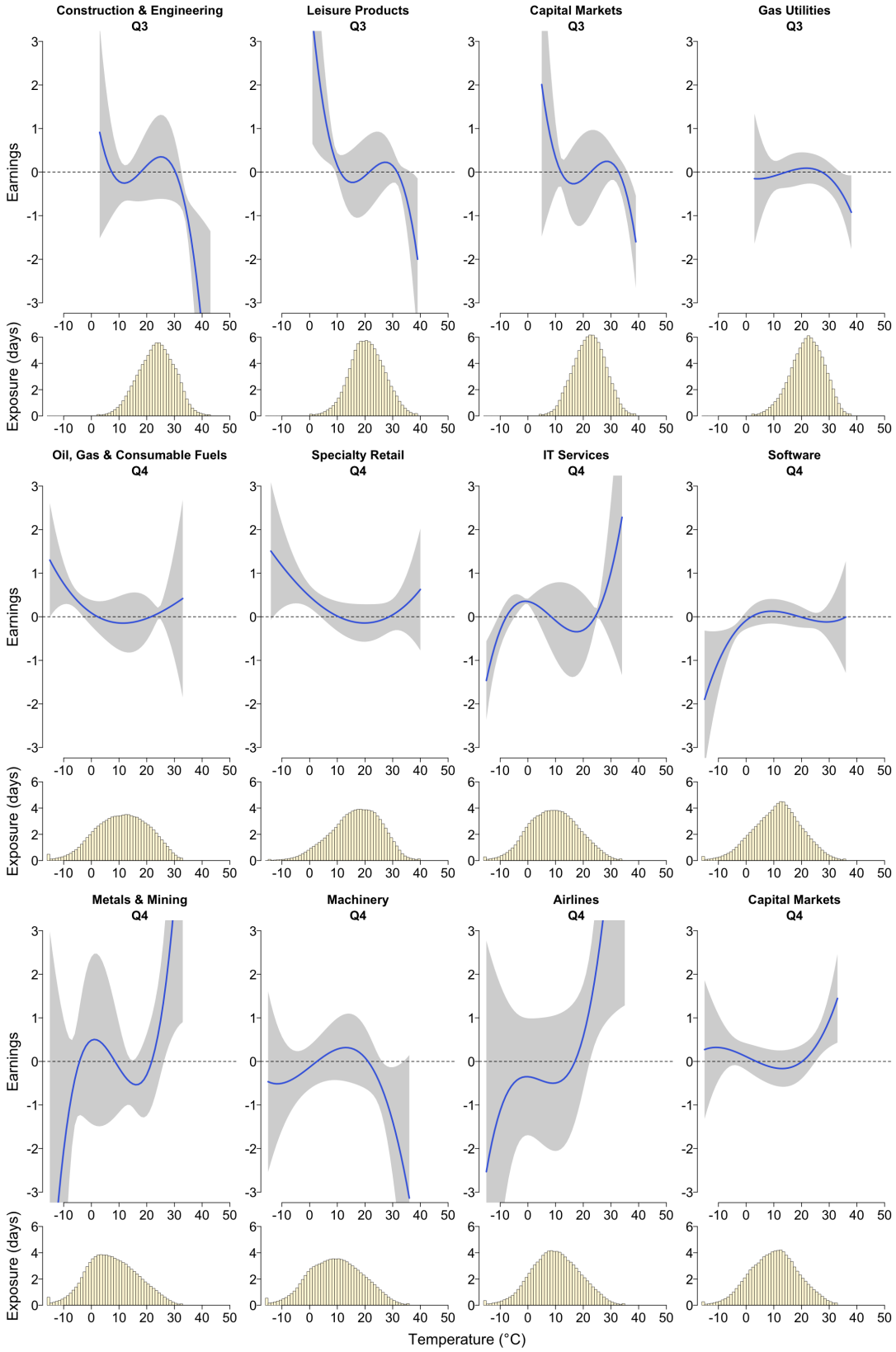


Figure 6

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 (equation 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 (Figure 5).

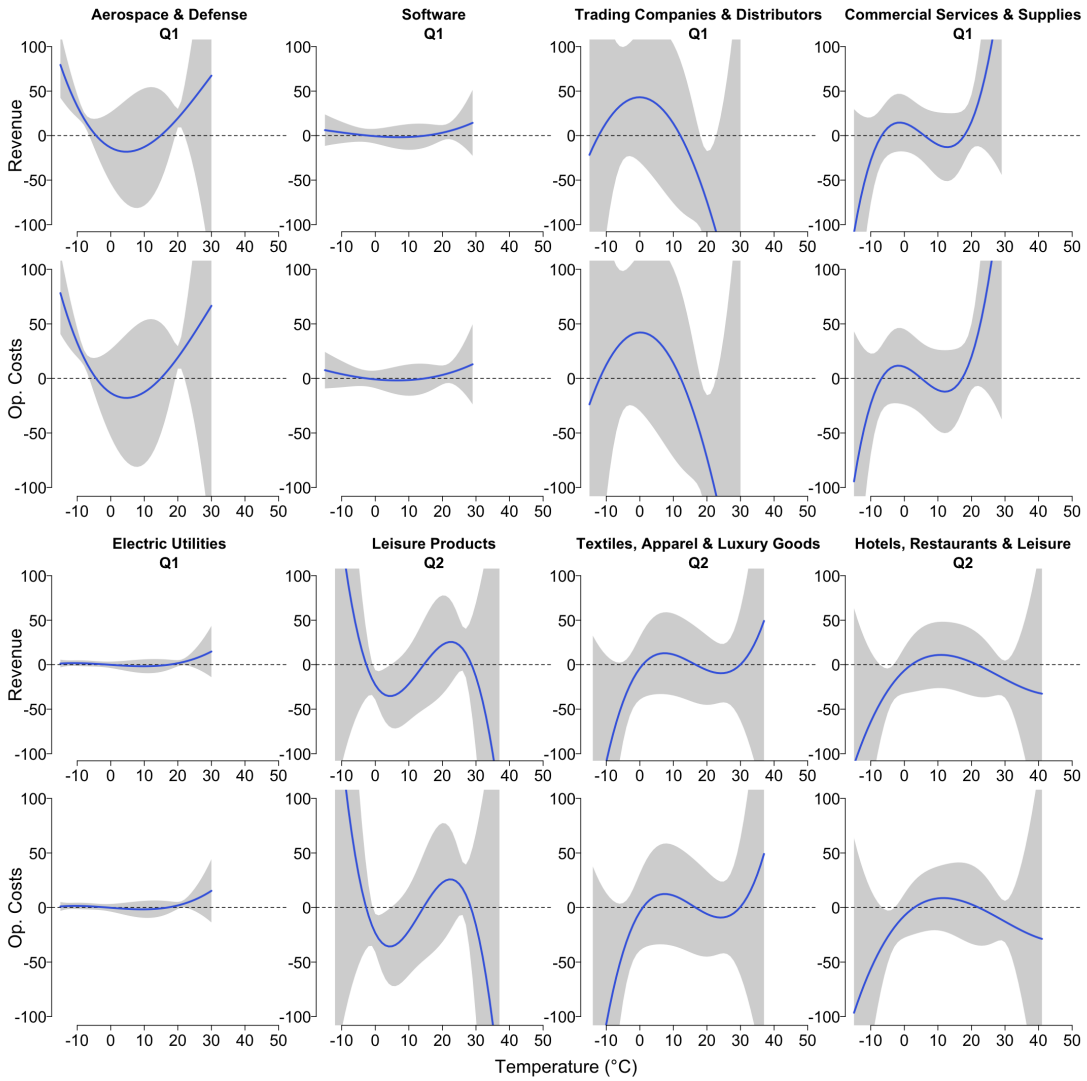
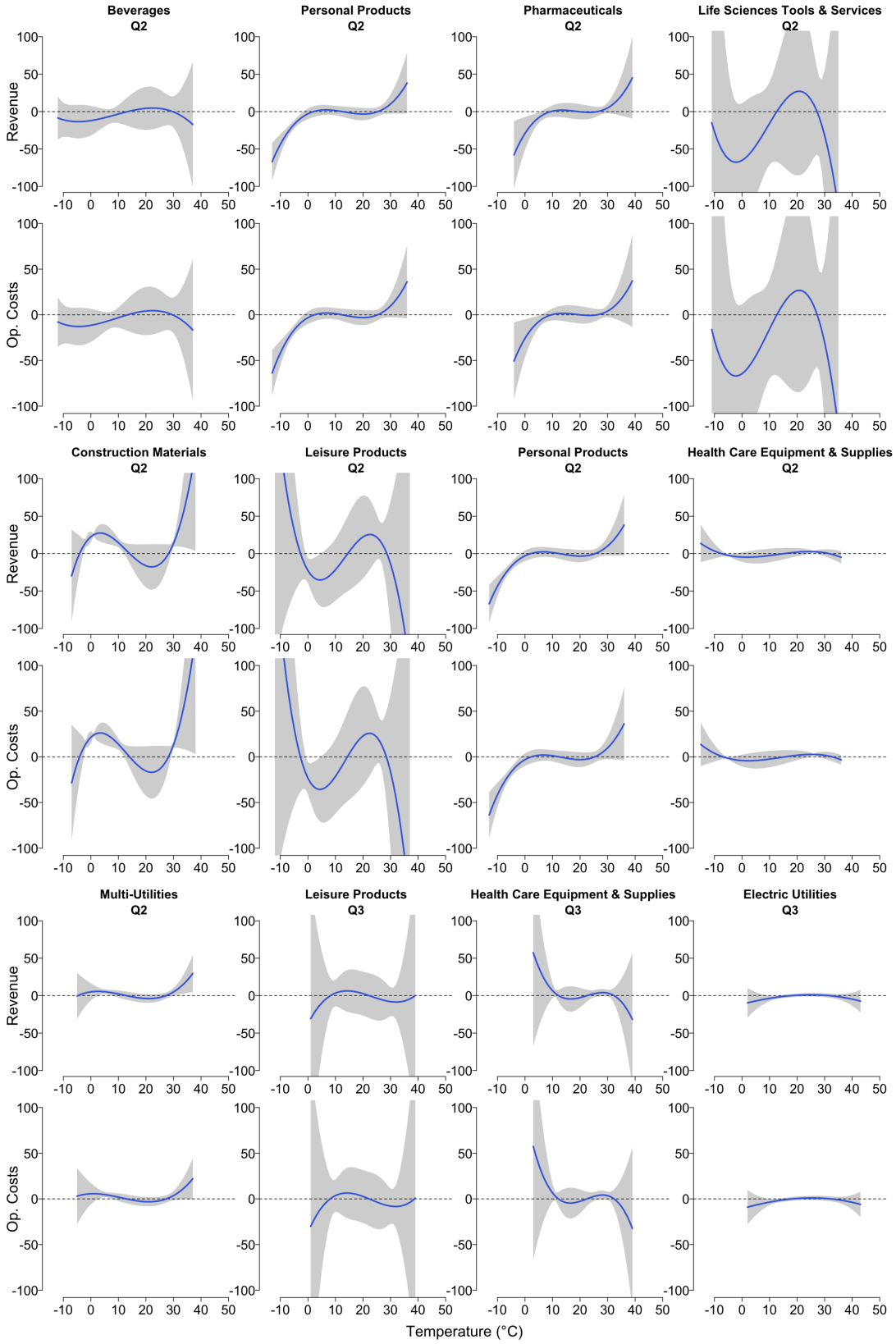


Figure 6 (Continued)



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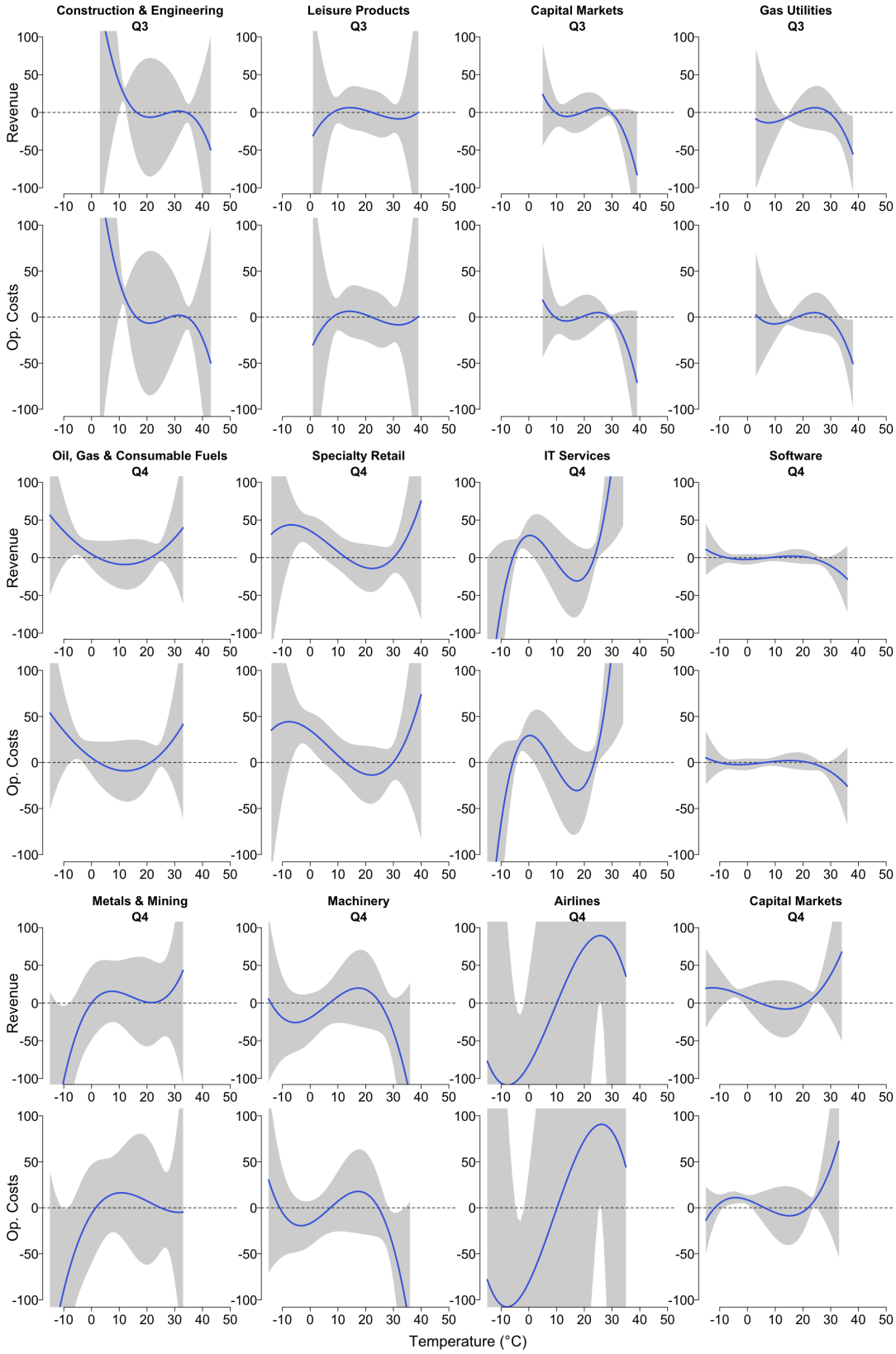
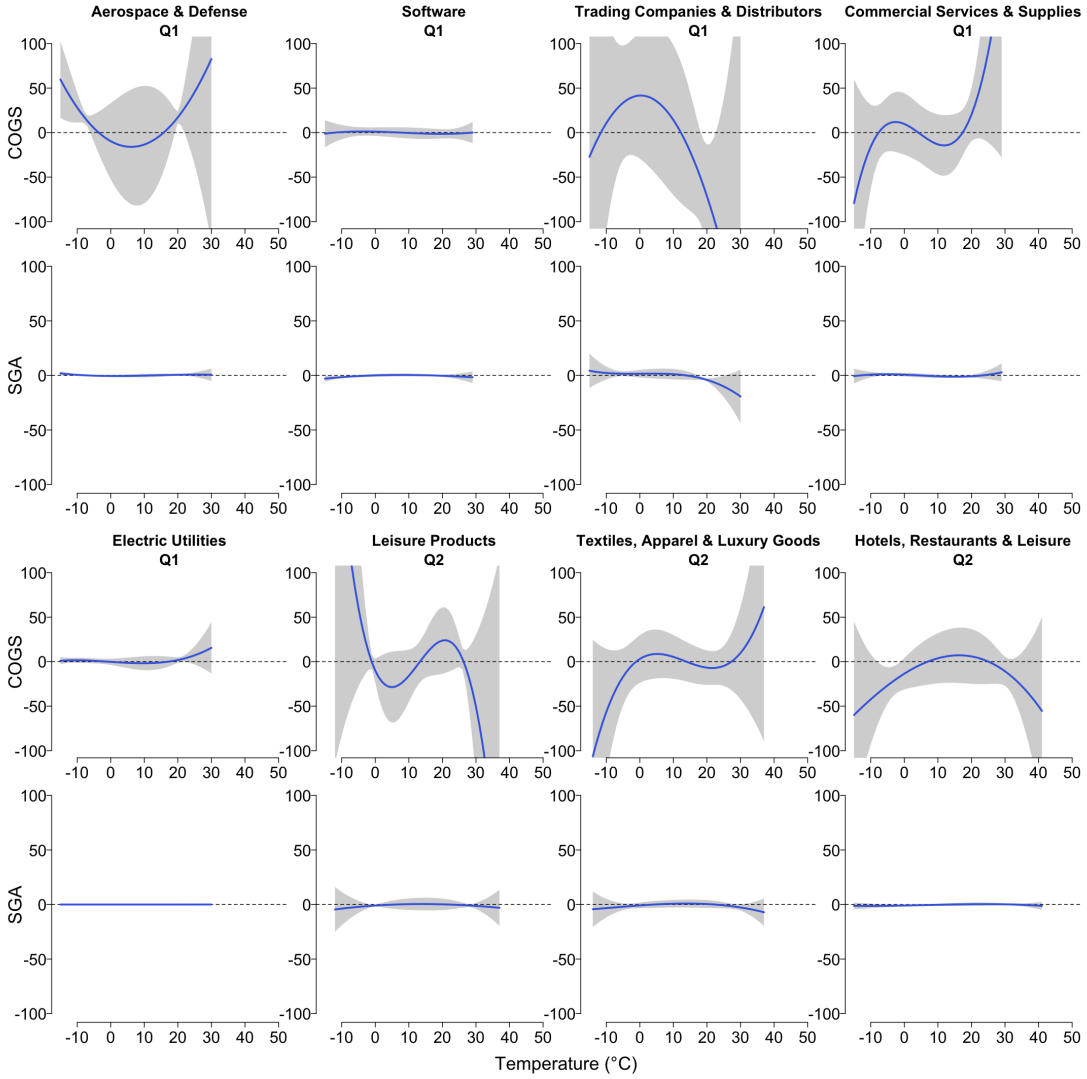


Figure 7

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 (equation 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 (Figure 5).



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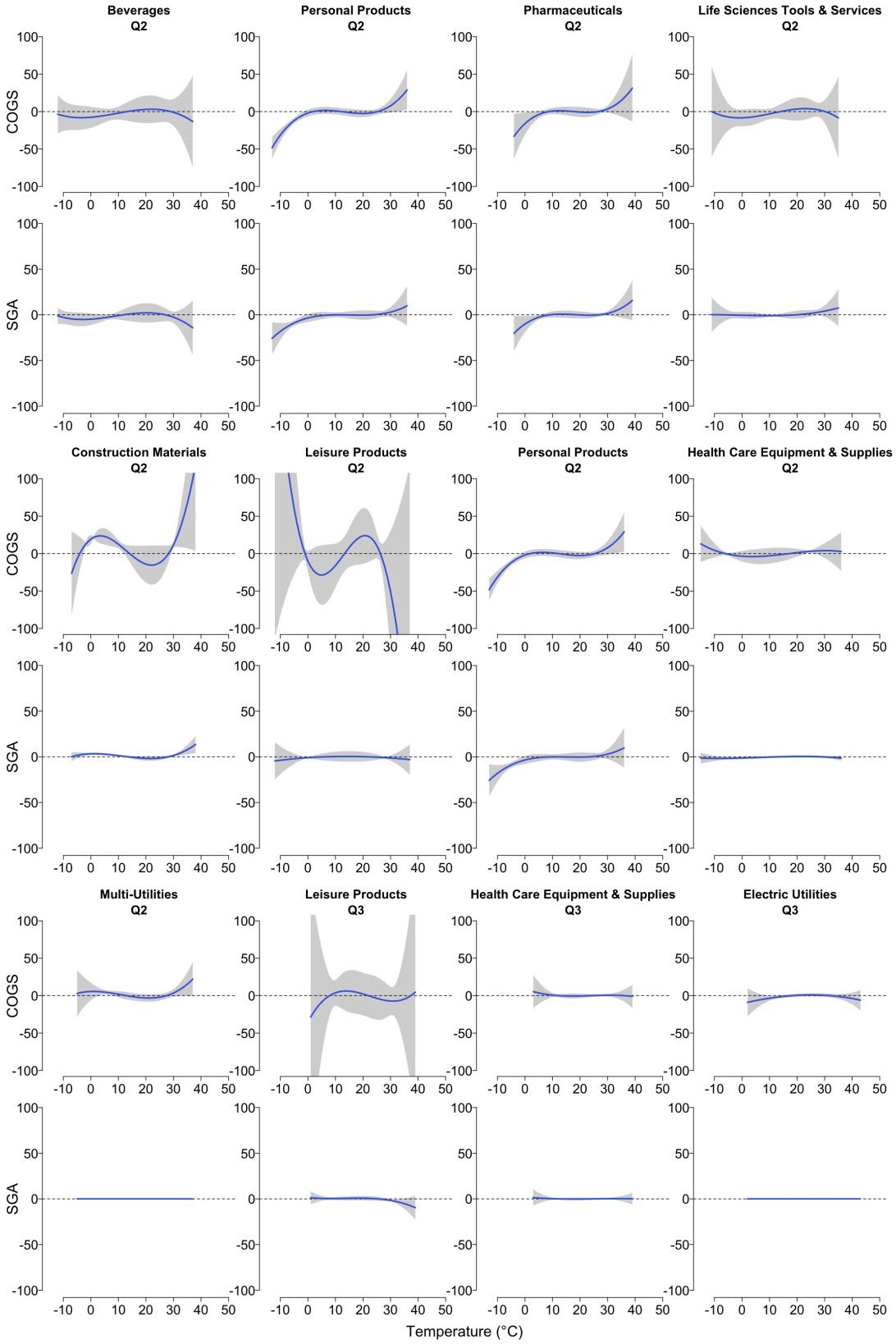

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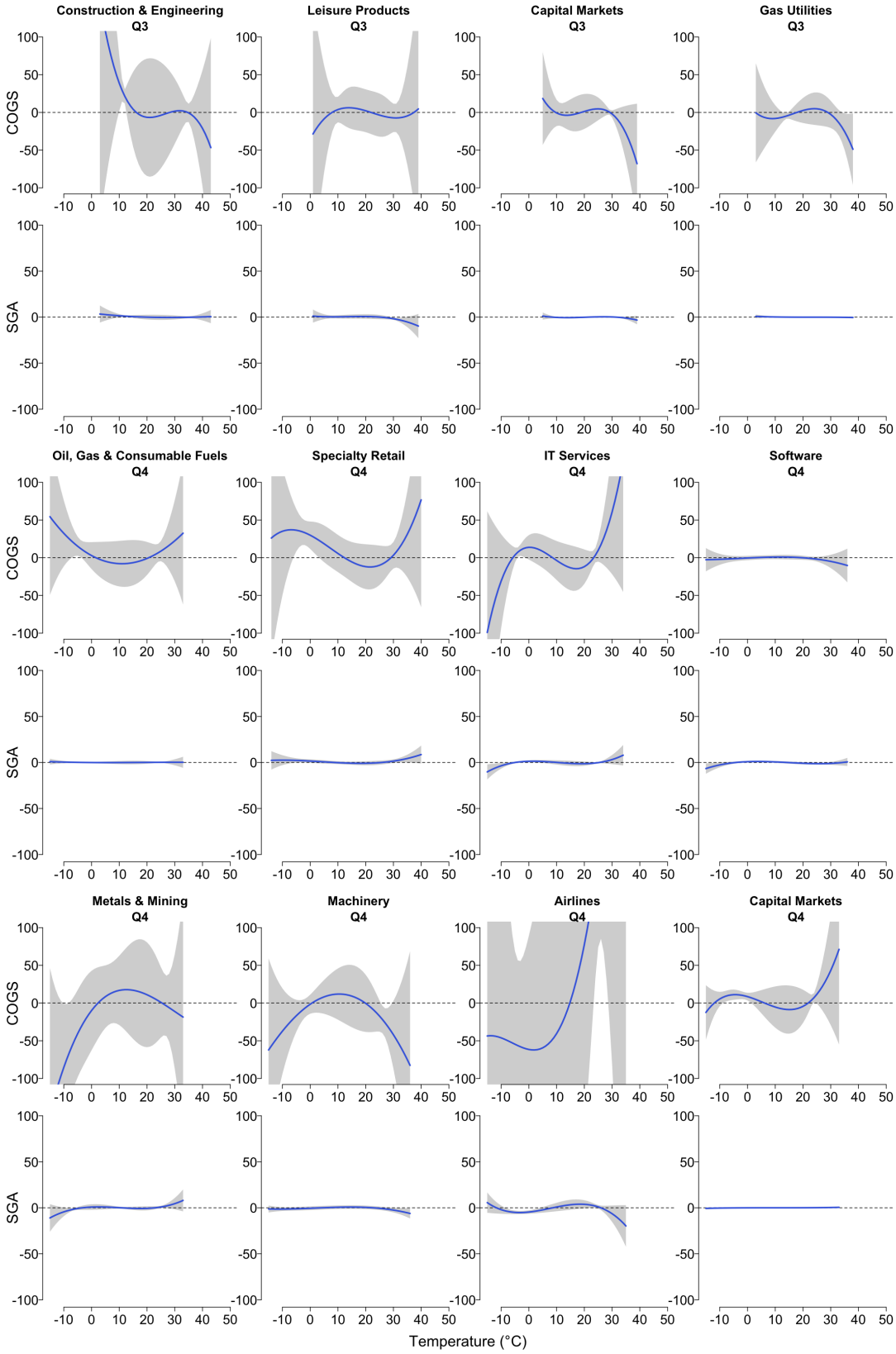
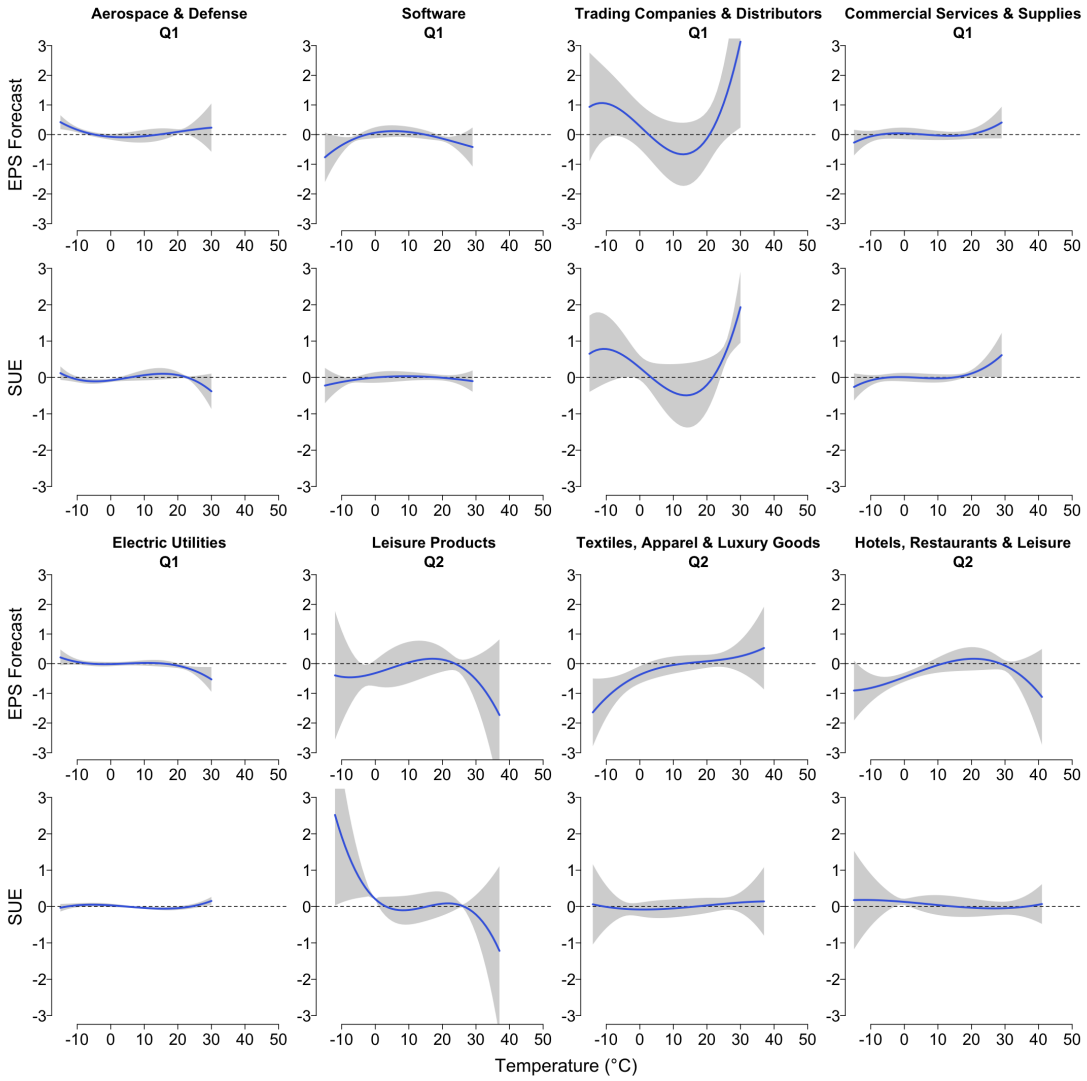


Figure 8

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 (equation 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 (Figure 5).



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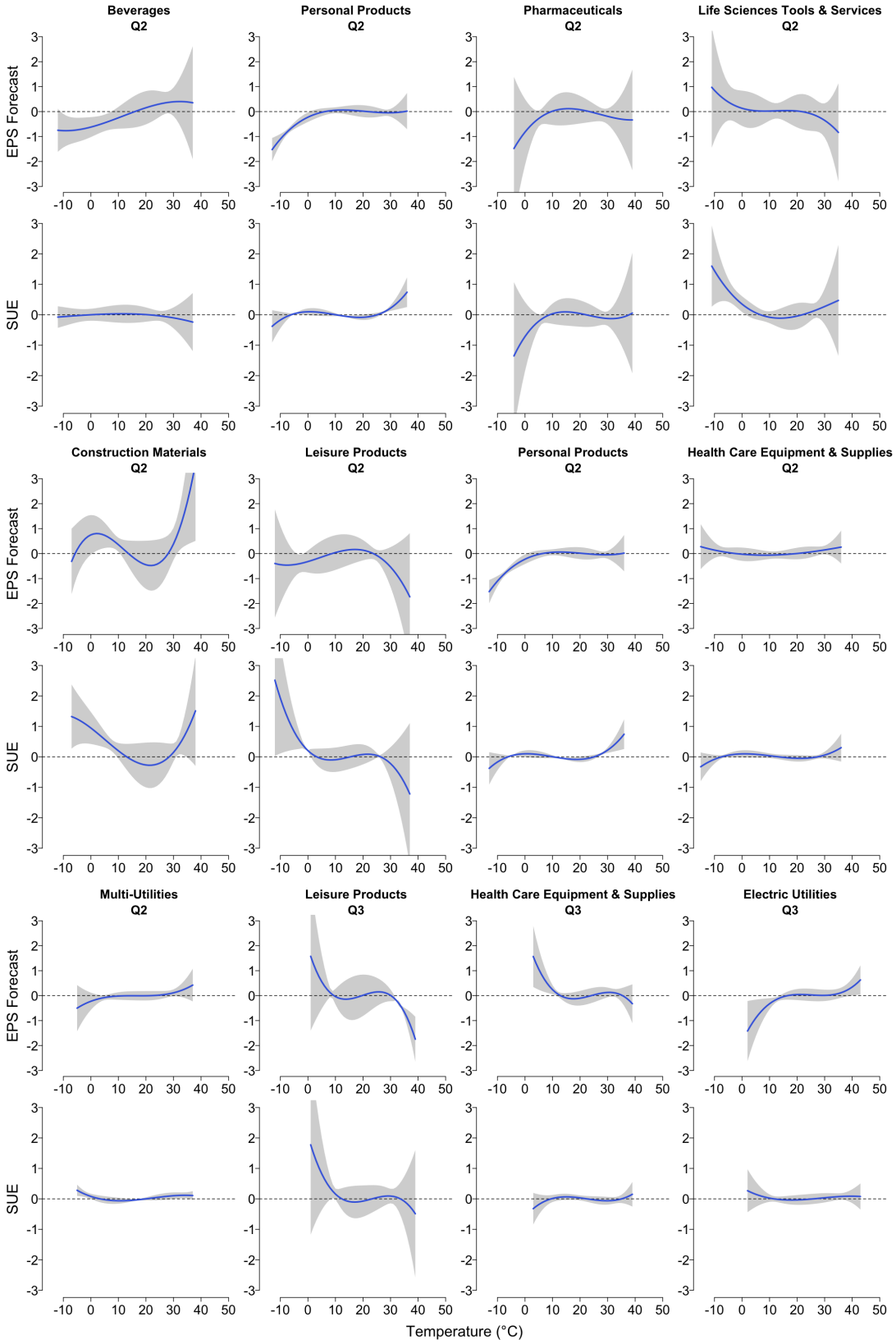

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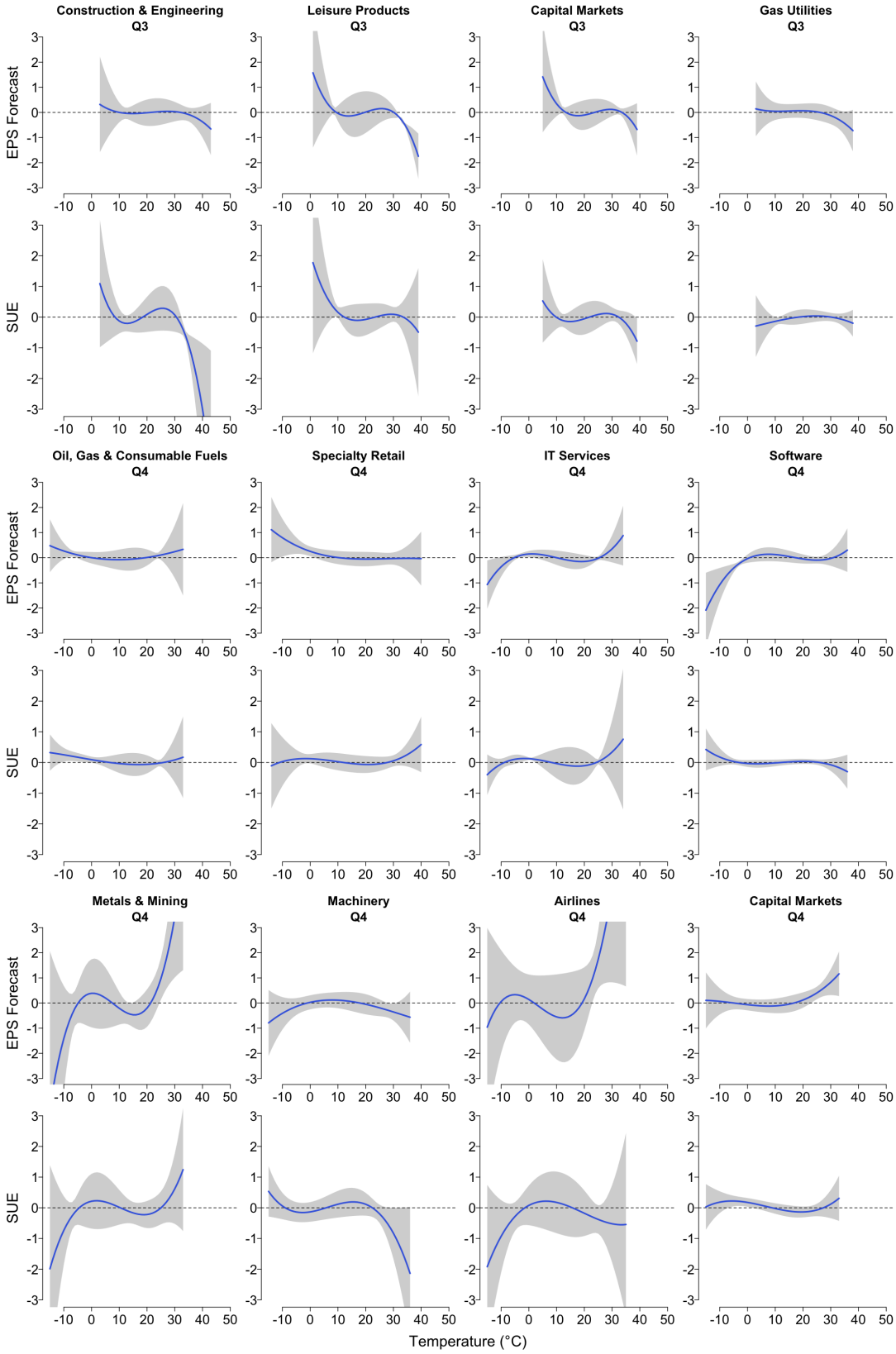


Figure 9

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.

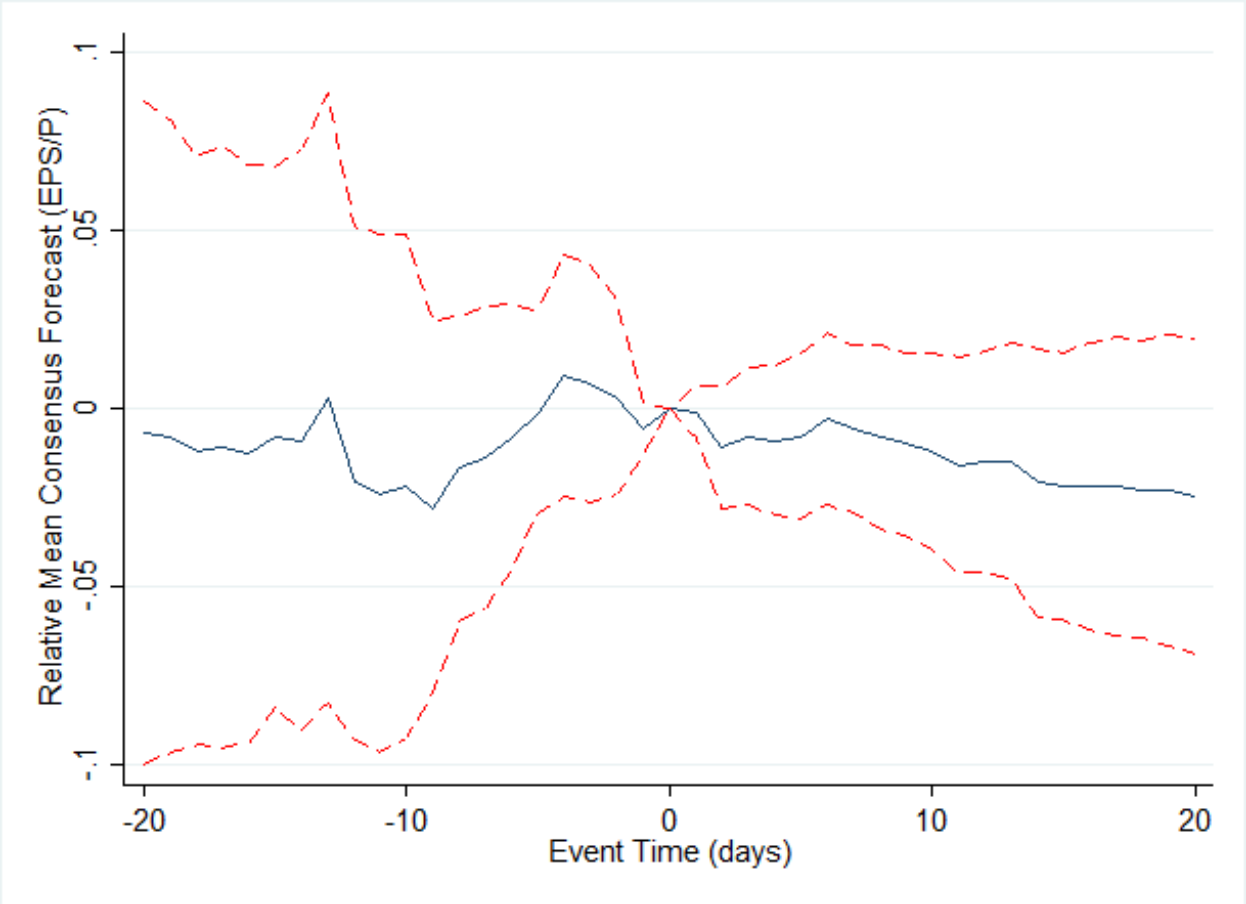
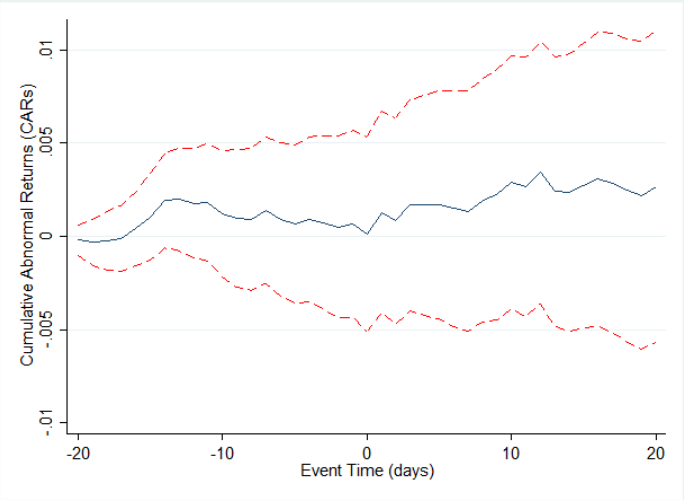


Figure 10

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. In Panel A, we consider all extreme temperature events in our sample. In Panel B, we plot results for the top (i.e., Pro-CC; dashed line) and bottom (i.e., Anti-CC; solid line) 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.

Panel A: All Extreme Temperature Events



Panel B: Extreme Temperature Events Sorted on Local Climate Change Beliefs