Temperature Shocks and Establishment Sales

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Combining granular daily data on temperatures across the continental United States with detailed establishment data from 1990 to 2015, we study the causal impact of temperature shocks on establishment sales and productivity. Using a large sample yielding precise estimates, we do not find evidence that temperature exposures significantly affect establishment-level sales or productivity, including among industries traditionally classified as "heat sensitive." At the firm level, we find that temperature exposures aggregated across firm establishments are generally unrelated to sales, productivity, and profitability. Our results support existing findings of a tenuous relation between temperature and aggregate economic growth in rich countries. (*JEL* G12, G14, Q54)

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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 the performance of the U.S. corporate sector. This lack of evidence comes with potentially important consequences. For example, the United States 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

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that action on climate change could help American workers and the economy (e.g. Rubin 2014; Stiglitz 2017). At the same time, political environments for climate policy among voters across the United States are diverse (Howe et al. 2015).

We aim to inform this debate by conducting the first study to provide direct evidence on how exposure to extreme temperatures affects U.S. corporate performance. Specifically, we estimate how location-specific temperature shocks affect establishment-level sales and productivity. We also go on to document the effect of temperature shocks on firm-level sales, productivity, and profitability.[1]

Our tests are motivated by a growing literature that examines the impact of temperature on a variety of economic outcomes. In particular, temperature has been shown to negatively affect aggregate output and income. For example, early cross-sectional studies show that countries with higher mean temperature exhibit lower levels and growth in per capita income (Gallup, Sachs, and Mellinger 1999; Dell, Jones, and Olken 2009). A more recent set of studies documents a similar negative effect on output using exogenous variation in location-specific temperature. In particular, Dell, Jones, and Olken (2012) use a panel of annual country-level observations to show that a 1°C increase in mean temperature reduces per capita income by 1.4 percentage points among developing countries. This finding is echoed by Hsiang (2010), who shows a similar negative effect on national output in a sample of 28 Caribbean countries. Although these studies provide suggestive evidence, research providing direct evidence on the link between temperature exposure and corporate performance in the United States is, to our knowledge, nonexistent. Our goal is to fill this gap by examining how temperature extremes affect establishment-level sales and productivity across the United States.

The climate economy literature also delineates channels through which extreme temperatures can affect sales and productivity. First, temperature extremes have been shown to affect 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. 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.

Second, a strand of literature establishes the link between extreme temperatures and agricultural outcomes. In particular, Fisher et al. (2012)

[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 one of the latest approaches in the climate impact literature (e.g. Dell, Jones, and Olken 2012, 2014), we focus on the impact of exogenous shifts in exposure to extreme temperatures at the annual and quarterly frequencies. However, we note that the effects we document should be interpreted with caution, in that responses to idiosyncratic temperature shocks might be different than the effects associated with permanent shifts in weather.

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 possible link between extreme temperatures and revenues in agricultural and related industries.

We begin by building a detailed panel of temperature exposures for economic establishments across the United States. We utilize a set of granular climate data that documents daily temperatures across 481,631 16-square-kilometer (i.e., 4×4 km.) 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.[2] We then combine the PRISM climate data with detailed data on U.S public firms' geographic footprints to generate measures of establishment-level weather exposure over the course of firms' fiscal years and quarters. To capture firms' geographic footprints, we obtain establishment-level data from the NETS database. This database provides addresses, as well information on sales and employment, for each U.S. establishment owned by a public company over the period from 1990 to 2015.

We ask how location-specific extreme temperature exposure affects establishment-level sales in the United States. Specifically, is the level of exposure to extreme temperatures a key driver of annual and quarterly sales growth? If so, are the predictive effects of extreme temperatures confined to heat-sensitive industries?

To answer this set of questions, we define several measures of temperature exposure using the matched PRISM weather and NETS establishment location data. First, we compute the average temperature experienced at each establishment location during a given fiscal period. Second, to capture exposure to extremes that may be masked in the average measure, we define absolute extreme temperature thresholds. In particular, we calculate the number of days in the fiscal period that temperatures exceed 30°C and fall below 0°C. Finally, because the definition of temperature extremes is likely to vary across geographies, we define location and time-specific extreme temperature exposure variables. Specifically, we calculate the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the PRISM grid-specific temperature distribution in a given month, and then aggregate over the months in a particular establishment's fiscal period. We also repeat this calculation using a more stringent definition of extreme temperatures, using the 95th and 5th percentiles of the location-specific temperature distributions.[3]

[2] 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.

[3] Our definition of temperature exposures is notably based on exceedances, measuring the number of days for which max/min temperatures exceed absolute or relative thresholds. This definition stands in contrast to an

Using these measures, we estimate the effect of temperature exposure on establishment-level sales by running panel regressions at the annual and quarterly frequencies. Following the climate economy literature (e.g. Dell, Jones, and Olken 2012, 2014), we regress the natural log of sales on each temperature exposure variable, and also include precipitation over the fiscal period as a control. We include industry-time fixed effects to control for broad trends in industry sales growth. More important, we also include establishment fixed effects in all specifications, which allow us to identify the causal effect of temperature exposure using random and exogenous variation in the distribution of heat around each firm's mean exposure over a fiscal period (Dell, Jones, and Olken 2014; Blanc and Schlenker 2017).

Our main finding is that the population average effect of temperature exposure on establishment-level sales growth is zero at both the annual and quarterly frequencies. That is, we find that shocks to establishment-level temperature exposures have a statistically insignificant effect on sales. Importantly, a priori power analyses indicate that our sample is sufficiently large such that statistical power issues are not a concern. In other words, our nonresults are driven by point estimates with small economic magnitudes, and not by imprecise estimates resulting from large standard errors. For example, we find that 1 extra day spent above 30°C is associated with a statistically insignificant 0.01-percentage-point increase in annual establishment sales.

We also examine whether our sales nonresults are potentially driven by establishments scaling labor inputs in order to smooth output. Specifically, we examine whether temperature exposure affects establishment productivity, measured as the ratio of sales to number of employees. We replace sales with productivity in our baseline regressions and do not find evidence that temperature exposures are significant drivers of worker productivity. This finding is consistent across our different temperature exposure variables and extends to both the annual and quarterly frequencies.

Next, we examine whether establishments in certain sectors of the economy exhibit climate sensitivity that differs from the population average. We define an indicator for establishments that are in the heat-sensitive industries identified by Graff-Zivin and Neidell (2014).[4] We reestimate our baseline specifications with an interaction between this indicator and the temperature exposure variables and find that establishment sales and productivity are generally unresponsive to temperature shocks across both heat-sensitive and non-heat-sensitive industries.

Given the importance of firm-level revenue and profitability among market participants, we also examine the impact of temperature exposures at firms' establishments on aggregate firm outcomes. Following our earlier analysis, we

alternative approach, where exposures are measured using time spent within different bins (e.g. Schlenker and Roberts 2009; Deschênes and Greenstone 2011).

4 These include agriculture; forestry, fishing, and hunting; mining; construction; manufacturing; and transportation and utilities.

focus on sales and productivity at the firm level. However, we also expand our scope to include measures of profitability including operating income, net income, and earnings announcement returns. To implement these tests, we compute firm-level temperature exposure variables by aggregating across firms' establishments. Specifically, for each firm-quarter, we take the sales-weighted average of mean temperature levels experienced at each of the firm's establishments during the fiscal quarter. Similarly, for the absolute and relative temperature exposure variables, we compute the sales-weighted average number of days spent above or below each of the cutoffs across each firm's establishments during the quarter.

Across our set of firm-level tests, we continue to find little evidence of a statistically or economically significant impact associated with temperature shocks. In particular, we do not find evidence that firm productivity is associated with our various temperature exposure measures. Similarly, we find a consistent set of nonresults when we examine the effect of temperature shocks on various measures of firm profitability.

We find similar nonresults in our firm sales regressions, where the majority of temperature measures have statistically insignificant loadings that are close to zero. However, one exception shows up when we regress firm sales on exposure to extreme cold temperatures, where we find a small but statistically significant population average effect. We analyze what drives this result and find that it is concentrated among firms in the energy sector. Specifically, we find that among Energy firms, an abnormal day of exposure to extreme cold is associated with about a 1.28- to 1.31-percentage-point increase in sales. In contrast, among firms in nonenergy sectors, there is generally no effect associated with extreme temperature exposures.

In our final set of tests, we conduct several important robustness checks. First, we analyze how our establishment-level results are affected by alternative standard error adjustments. Specifically, we assess whether the inferences we make in our tests using double-clustered standard errors are affected by spatial correlation in regression errors. We implement a spatial correlation adjustment following the approach of Conley (1999) and find that the resultant t-statistics are less conservative than those used in our baseline tests. Second, noting that the distance between firms is not well defined, we develop and implement a modified Conley approach that accounts for the proximity of firms' geographic footprints in our firm sales regressions. As in our establishment-level comparison, we find that our baseline approach of using double-clustered standard errors is the more conservative one. Finally, we consider whether establishments in relatively warmer areas of the United States exhibit temperature sensitivity that differs from their counterparts in cooler parts of the country. We find limited evidence in support of this adaptation story.

Our study primarily contributes to the body of research in science and economics documenting the effects of temperature shocks and extreme weather events on various outcomes. For example, studies show that the negative impacts of extreme temperatures extend to labor supply (Graff-Zivin and Neidell 2012, 2014), agricultural outcomes (Schlenker and Roberts 2009; Fisher et al. 2012; Ortiz-Bobea, Knippenberg, and Chambers 2018), 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 recent 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 the effect of abnormal temperature exposures on establishment sales and productivity, as well as firm-level sales, productivity, and profitability. Although our set of nonresults may seem at odds with existing findings of a negative relationship between temperature and aggregate output (e.g. Gallup, Sachs, and Mellinger 1999; Dell, Jones, and Olken 2009; Hsiang 2010; Burke, Hsiang, and Miguel 2015), we note that our study focuses on establishments owned by publicly listed firms in the United States, a group likely to have the resources to withstand extreme weather. Consistent with this idea, Dell, Jones, and Olken (2012) find that the negative impact of temperature is concentrated among developing countries. In contrast, higher temperatures have no discernable impact on economic growth among the richer countries in their sample.

Our study also contributes to a strand of literature in finance and economics examining the determinants of establishment-level sales and productivity. For example, Alfaro and Chen (2012) examine the moderating effect of foreign ownership on establishment sales following the 2008 financial crisis. Midrigan and Xu (2014) study how financial frictions affect plant-level productivity. Giroud (2013) demonstrates that proximity to headquarters serves to boost plant-level investment and productivity. Our paper adds to this literature by documenting how temperature shocks affect establishment sales and productivity.

1. Methodology and Research Design

1.1 Hypothesis development

Our main hypotheses are based on the idea that abnormal exposure to temperature extremes is likely to affect sales growth among local economic establishments. This conjecture is based on suggestive evidence from the climate economy literature. In particular, Jones and Olken (2010) and Dell, Jones, and Olken (2012) demonstrate the negative impact of temperature shocks on gross domestic product (GDP) growth and exports across a large sample of countries. They suggest two channels through which climate shocks affect economic output: (1) decreased labor supply amid extremely high temperatures, especially in sectors with high climate exposure (e.g., light manufacturing), and (2) agriculture and food-related industries sensitive to temperature extremes.

The labor supply channel is consistent with the age-old idea that laborers are less productive when temperatures are extremely high (Huntington, 1915). Linking the American Time Use Survey to regional weather data, Graff-Zivin and Neidell (2014) find that hot temperatures reduce hours worked in industries with high climate exposure.[5] The agricultural channel arises from the fact that crops stop growing, and can even die, when exposed to extreme temperatures. In particular, Fisher et al. (2012) and Schlenker and Roberts (2009) find that extreme temperatures hurt crop yields, especially above certain crop-specific thresholds.

Taken together, the evidence from the climate economy literature suggests the following testable hypotheses:

Hypothesis 1: Greater exposure to extreme temperatures will result in lower establishment-level sales.

Hypothesis 2: Greater exposure to extreme temperatures will result in lower establishment-level productivity.

Hypothesis 3: The negative effects of greater extreme temperature exposure on sales and productivity will be more pronounced for establishments in industries with high climate exposure, including the agricultural industry.

1.2 Data description

To examine the relationships between temperature exposure and establishment performance measures, 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-sq.-km. (i.e., 4×4 km.) grids covering the continental United States. Figure 1 presents an example of the grids for Tompkins County, New York.

We calculate several temperature exposure variables for each grid location each month. First, we calculate the average monthly temperature in each grid location. Second, we calculate the number of days during the month that temperatures exceed 30°C and fall below 0°C. Third, and finally, we calculate location and time-specific extreme temperature exposure variables. Specifically, we calculate the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the grid location-specific

[5] Using the National Institute for Occupational Safety and Health's definition of heat-exposed industries, Graff-Zivin and Neidell (2014) separate industries into high versus low climate exposure categories. High climate exposure industries are those in which 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.

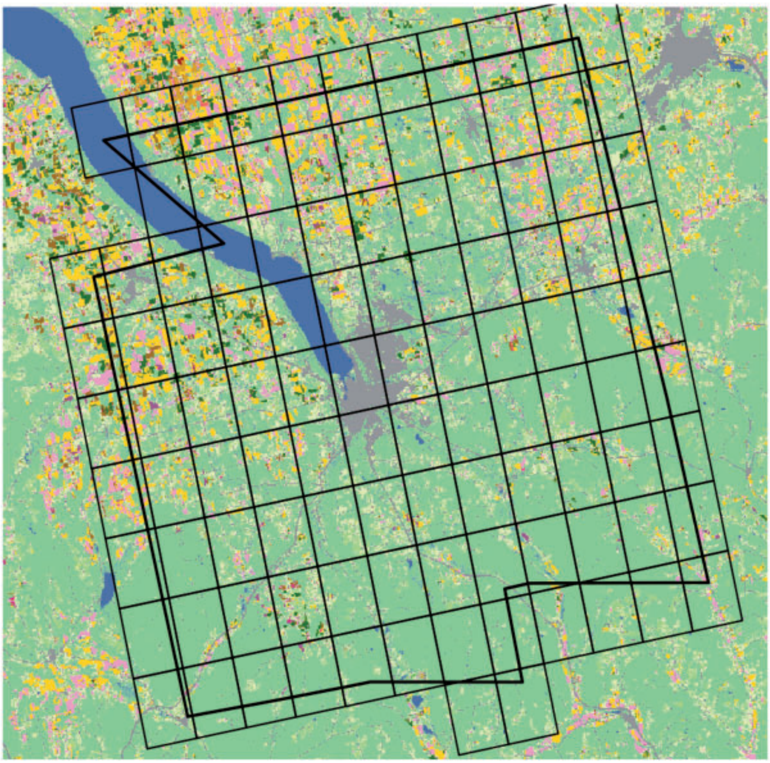

Figure 1
PRISM weather grids
The figure overlays a topographic map of Tompkins County, New York (1,274 sq. km.), with a 4×4 km. grid corresponding to weather data. The grids and weather data come from the PRISM Climate Group at the Oregon State University. Daily grid-level data on minimum, maximum, and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

temperature distribution in a particular month. We also repeat this for a more stringent definition of extreme temperatures, using the 95th and 5th percentiles of the temperature distributions.

Figure 2 illustrates the grid-level temperature exposure data. Panel A displays grid-level exposures (in days) to temperatures above 30°C across the United States in July of 1999. Panel B presents grid-level exposures relative to the historical mean number of days spent above 30°C in July.

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. 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

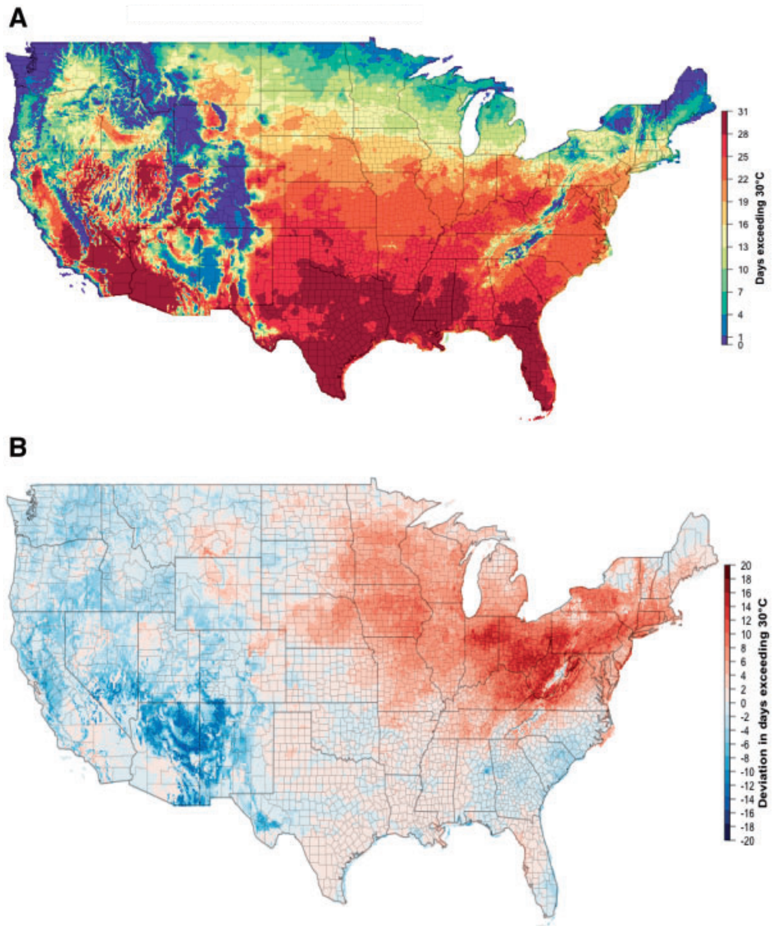

Figure 2
Grid-level exposure to temperatures above 30°C
The figure plots the number of days for which the maximum temperature exceeded 30°C for 4×4 km. grids across the continental United States. In panel A, the exposures are measured as the number of days that the maximum temperature exceeded 30°C during the month of July 1999. In panel B, the exposures are measured as the deviation, relative to the historical mean, in the number of days that the maximum temperature exceeded 30°C during the month of July 1999. Grid-level temperature data come from the PRISM Climate Group at the Oregon State University. (A) Days with temperatures above 30°C, July 1999. (B) Deviation in day with temperatures above 30°C (days relative to historical mean), July 1999.

allows us to track the sales and productivity of workers at each establishment over time, as well as the economic importance of a firm's establishments to its overall performance.[6] Figure 3 displays the establishment locations owned by all publicly traded U.S. firms in our sample during the sample period.

6 It is important to note that a large proportion of establishment-level sales figures in the NETS data are imputed by either Dun & Bradstreet or Walls & Associates. While random measurement error in our dependent variables

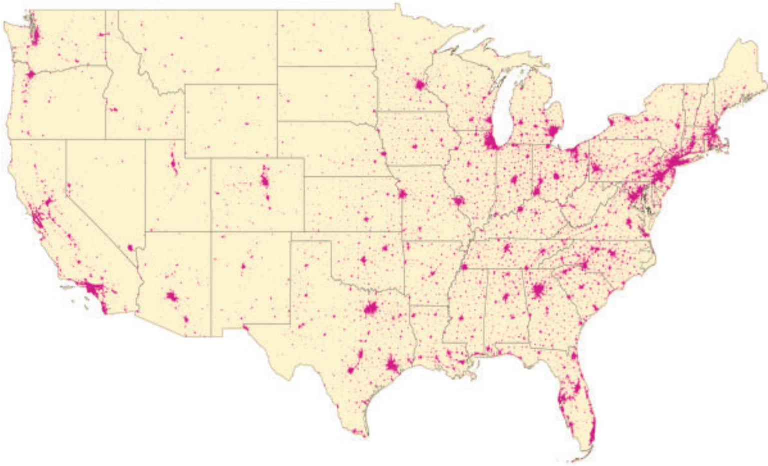

Figure 3
Establishment locations for U.S. publicly listed firms
The figure plots the locations of establishments owned by publicly traded U.S. firms in our sample. Establishment locations come from the NETS Publicly Listed Database, produced by Wall & Associates. The sample period is 1990 to 2015.

We match the PRISM-based temperature exposure and establishment location data to construct establishment and firm-level temperature exposure variables at the quarterly and annual frequencies. First, we verify the geographic coordinates of each firm establishment location address using Google Maps. We then match these coordinates to a specific 4×4 km. PRISM cell to capture temperature exposure at a given establishment in a given month. We aggregate establishment-level temperature exposure variables over the three month intervals that make up the parent firm's fiscal quarter.[7] To calculate firm-level temperature variables, we calculate sales-weighted averages across each firm's establishment locations.[8] Finally, we aggregate over the four quarters in a fiscal year to calculate annual temperature variables.

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

of interest will not lead to biased estimates, we verify our main results using a subsample of establishment sales that are actual values reported by firms. Furthermore, our firm-level sales and productivity regressions can be viewed as additional robustness checks on this dimension, because firm-level sales data are directly reported by firms and not imputed.

7 For example, for a firm with fiscal quarter ending on March 31, we aggregate monthly firm-level temperature exposures over January, February, and March. Similarly, for a firm with fiscal quarter ending on April 30, we aggregate the temperature exposures over February, March, and April, and so on.

8 As a robustness check, we verify our main results using different weighting schemes, including weights based on the number of employees and equal weights.

then aggregate the monthly establishment-level precipitation variable over 3-month intervals matching parent firms' fiscal quarters, as well as over the quarters of each fiscal year. Finally, we compute a firm-level precipitation variable by taking the sales-weighted average across establishments.

To analyze how exposure to extreme temperatures affects firm-level profitability, we further collect data on quarterly operating income and net income from Compustat. To aid in interpretation, we scale each of these measures by beginning-of-quarter total assets and then take the natural log of one plus the resultant value. Finally, as a measure of the surprise component of quarterly earnings, we calculate stock returns around earnings announcements using data on common stock prices and returns for firms trading on the AMEX, Nasdaq, and NYSE exchanges from CRSP and earnings announcement dates from the Thomson Reuters IBES database.

Table 1 reports summary statistics for key variables in the matched sample of financial and weather exposure variables. Panel A shows the mean, standard deviation, median, and first and third quartiles for the establishment-level sales and productivity measures, as well as our temperature exposure and precipitation measures. Temperatures are reported in degrees Celsius, time-based temperature exposures are measured in days, and precipitation is reported in hundreds of millimeters. Panel B reports the same summary statistics for firm-level measures. In both panels A and B, the top subpanel presents summary

Table 1
Summary statistics

	A. Establishment-level variables				
	Mean	SD	1st quartile	Median	3rd quartile
Annual frequency					
Sales	14.45	1.73	13.20	14.24	15.57
Productivity	11.61	0.67	11.28	11.54	11.94
Mean temperature (°C)	14.48	4.50	10.89	13.87	17.89
Days above 30°C	68.51	49.39	27	57	108
Days below 0°C	74.39	52.16	23	80	117
Days above 90th pctl	36.85	16.28	25	35	46
Days below 10th pctl	34.88	13.50	26	34	43
Days above 95th pctl	18.59	10.65	11	17	24
Days below 5th pctl	17.27	8.66	11	16	22
Precipitation (mm/100)	10.12	4.19	7.82	10.62	12.84
Quarterly frequency					
Sales	13.05	1.76	11.80	12.85	14.18
Productivity	10.21	0.72	9.87	10.17	10.57
Mean temperature (°C)	14.48	8.58	7.73	15.65	21.31
Days above 30°C	17.13	24.19	0	5	26
Days below 0°C	18.60	25.72	0	3	34
Days above 90th pctl	9.21	6.30	5	8	13
Days below 10th pctl	8.72	5.79	5	8	12
Days above 95th pctl	4.65	4.19	2	4	7
Days below 5th pctl	4.32	3.84	1	3	6
Precipitation (mm/100)	2.53	1.50	1.50	2.45	3.39

(*Continued*)

Table 1
(Continued)

	B. Firm-level variables				
	Mean	SD	1st quartile	Median	3rd quartile
Annual frequency					
Sales	17.35	2.39	15.82	17.42	18.99
Productivity	11.79	0.82	11.40	11.71	12.10
Mean temperature (°C)	14.33	3.25	12.25	14.16	16.12
Days above 30°C	61.71	35.55	35.24	58.00	80.20
Days below 0°C	71.22	39.95	45.68	73.03	96.15
Days above 90th pctl	36.05	12.33	27.75	35.00	43.27
Days below 10th pctl	36.54	11.89	29.03	35.00	44.00
Days above 95th pctl	18.12	7.90	13.00	17.15	22.29
Days below 5th pctl	18.30	7.54	13.30	17.11	22.94
Precipitation (mm/100)	9.63	3.10	8.12	9.92	11.40
Quarterly frequency					
Sales	15.92	2.57	14.42	16.04	17.61
Productivity	10.35	1.04	9.98	10.32	10.73
Operating income	0.01	0.06	0.00	0.02	0.03
Net income	−0.01	0.07	0.00	0.01	0.02
Earnings ann. returns	0.00	0.10	−0.04	0.00	0.04
Mean temperature (°C)	14.33	7.67	8.15	15.12	20.86
Days above 30°C	15.48	20.05	0.23	5.73	25.00
Days below 0°C	17.87	22.25	0.00	5.09	32.37
Days above 90th pctl	9.04	4.81	5.94	8.48	11.64
Days below 10th pctl	9.17	4.94	5.83	8.34	11.77
Days above 95th pctl	4.55	3.12	2.38	4.02	6.00
Days below 5th pctl	4.59	3.29	2.19	4.00	6.07
Precipitation (mm/100)	2.41	1.10	1.79	2.39	3.00

This table reports summary statistics for key variables in the study. Panel A presents summary statistics for establishment-level variables at both the annual and the quarterly frequencies. Sales is the natural log of establishment sales. Productivity is the natural log of the ratio of sales to the number of employees in a particular establishment. Panel B presents summary statistics for firm-level variables at both annual and quarterly frequencies. Sales is the natural log of total sales across a firm's establishments. Productivity is the natural log of the ratio of sales to total employees across a firm's establishments. Operating income is the natural log of one plus quarterly operating income before depreciation scaled by total assets. Net income is the natural log of one plus quarterly net income scaled by total assets. Earnings announcement returns are defined as the abnormal stock return from the [0,+3]-day window surrounding earnings announcements, where day 0 is the announcement date. Section 1.2 defines temperature and precipitation variables. Temperatures are reported in degrees Celsius; temperature exposure measures are reported in days; and precipitation is reported in hundreds of millimeters.

statistics at the annual frequency, and the bottom subpanel focuses on quarterly variables.

1.3 Empirical methodology

To test the relationship between temperature and performance, we focus on regressions of establishment-level sales on temperature exposure variables. Following the climate economy literature closely (e.g. Dell, Jones, and Olken 2012, 2014), we posit the following form for the annual sales process in each year t:

$$sales_{i,j,t} = \theta_i + \theta_{j,t} + \rho T_{i,t} + \gamma P_{i,t} + \varepsilon_{i,j,t}, \tag{1}$$

where $sales_{i,j,t}$ measures the natural log of sales at establishment i, with parent firm in industry j, during year t. $T_{i,t}$ and $P_{i,t}$ are the temperature exposure and precipitation variables at the establishment location over year t.

To capture broad trends in industry sales, we include industry-year fixed effects ($\theta_{j,t}$). More important, we also include establishment fixed effects, captured by θ_i, which allow us to identify the causal effect of temperature exposure using random and exogenous variation in the distribution of heat around each firm's mean annual exposure (Dell, Jones, and Olken 2014; Blanc and Schlenker 2017). Following Dell, Jones, and Olken (2014), we do not further include establishment- or firm-level control variables in our regressions in order to avoid so-called "overcontrolling" problems.

We also estimate an analogous set of sales regressions at the quarterly frequency. These specifications take the following form, where time index t now indexes fiscal quarters:

$$sales_{i,j,t} = \theta_{i,q} + \theta_{j,t} + \rho T_{i,t} + \gamma P_{i,t} + \varepsilon_{i,j,t}. \tag{2}$$

$sales_{i,j,t}$ measures the natural log of sales at establishment i, with parent firm in industry j, during quarter t. $T_{i,t}$ and $P_{i,t}$ are the temperature exposure and precipitation variables at the establishment location over quarter t. $\theta_{j,t}$ captures broad quarterly trends in industry sales. To account for potential seasonality in sales and estimate the effect of year-to-year variation in quarterly weather on sales, we replace establishment fixed effects with establishment-by-calendar-quarter fixed effects, given by $\theta_{i,q}$. In both annual and quarterly regressions, $\varepsilon_{i,j,t}$ is an error term that, in our baseline specifications, is clustered both by the establishment and across time.[9]

2. Main Empirical Tests and Results

2.1 Do temperature exposures affect establishment sales?

We begin by asking whether temperature exposure affects sales across economic establishments in the United States. Table 2, panel A, presents estimates from regressions of the form outlined in Equation (1) at the annual frequency.[10]

In Column 1, we regress establishment sales on mean temperature over the year. The estimated effect is economically small and statistically insignificant. A 1°C increase in mean temperature is associated with just a 0.11-percentage-point increase in sales, an estimate that is not significantly different from zero. In Column 2, we include a measure of extremely hot days for which temperatures exceed an upper limit of 30°C, as well as a measure of extremely cold days for which the temperature drops below 0°C. As with the mean temperature measure,

[9] We also consider an alternative approach whereby we adjust for spatial and serial correlation in errors using the respective approaches of Conley (1999) and Newey and West (1987). However, we find that double-clustered standard errors yield more conservative inferences. See Section 4.1 for details.

[10] Given the potential for nonresults, we consider an a priori analysis of the power of our statistical tests. In particular, we note that for our annual establishment-level regressions with both establishment and industry-year fixed effects, we would need about 170,000 observations to detect a tiny effect of just 0.01 percentage points, with a significance level of 5% and 90% power. This requirement is comparatively small in relation to our sample of over 1.38 million observations, suggesting that our tests have sufficient power to reject the null.

Table 2
Establishment-level sales regressions

	A. Annual frequency				*B. Quarterly frequency*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	0.0011				0.0009			
	(0.37)				(0.58)			
Days above 30°C		0.0001				0.0001		
		(1.20)				(0.71)		
Days below 0°C		0.0002				0.0001		
		(0.80)				(0.27)		
Days above 90th pctl			0.0001				0.0002	
			(0.91)				(1.10)	
Days below 10th pctl			0.0000				−0.0001	
			(−0.22)				(−0.57)	
Days above 95th pctl				0.0001				0.0002
				(0.65)				(0.93)
Days below 5th pctl				−0.0001				−0.0003
				(−0.49)				(−0.84)
Precipitation	−0.0006	−0.0004	−0.0005	−0.0006	−0.0014	−0.0013	−0.0012	−0.0014
	(−1.16)	(−0.68)	(−0.99)	(−1.15)	(−1.71)	(−1.47)	(−1.52)	(−1.63)
Establishment FE	Yes	Yes	Yes	Yes	No	No	No	No
Estab-calendar qtr FE	No	No	No	No	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.915	.915	.915	.915	.895	.895	.895	.895
No. observations	1,385,344	1,385,344	1,385,344	1,385,344	5,541,606	5,541,606	5,541,606	5,541,606
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. The dependent variable in all specifications is the natural log of sales. Panel A presents estimates at the annual frequency based on Equation (1). Panel B presents estimates at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include either establishment (annual) or establishment-by-calendar-quarter (quarterly) fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering on both the establishment and time dimensions.

we do not find evidence of a significant relation between an establishment's exposure to extreme temperatures and its sales. In particular, 1 extra day spent above 30°C is associated with a statistically insignificant 0.01-percentage-point increase in annual establishment sales.

In Column 3, we adopt relative measures of temperature extremes and define extremely hot days as the number of days for which the maximum temperature exceeds the 90th percentile of the historical monthly distribution of daily temperatures in an establishment location. Similarly, extremely cold days are defined as the number of days that are colder than the 10th percentile in the historical distribution. The regression results show no evidence that establishment-level sales are significantly related to extremely hot or cold days. In Column 4, we repeat the exercise after adjusting the hot day cutoff to the 95th percentile and the cold day cutoff to the 5th percentile of the location-specific temperature distributions. Again, we do not find evidence that sales are related to extremely hot or cold days.

In Table 2, panel B, we turn to regressions at the quarterly frequency, as outlined in Equation (2). In these specifications, we use weather variation over firms' fiscal quarters to estimate the effect of temperature exposure on quarterly sales. Importantly, we include establishment-by-calendar-quarter fixed effects in our regressions, so that the effects of temperature exposure are identified using within-season variation in temperature variables for each establishment over time. We calculate quarterly establishment-level sales by multiplying the proportion of annual firm-level revenues recorded by Compustat in a given fiscal quarter by annual sales for each of the firm's establishments reported in the NETS database.

We find similar results to those in our annual regressions. Specifically, we do not find evidence of a statistically significant relationship between an establishment's quarterly sales and the mean temperature in the quarter. There is also no evidence that establishment sales are related to days exposed to extreme temperatures above or below fixed cutoffs of 30°C and 0°C. When we define extreme temperatures as the number of days for which an establishment is exposed to temperatures above the 90th or 95th percentile or below the 10th or 5th percentile relative to the historical distribution, the results remain unchanged. Specifically, we find that quarterly establishment sales are unrelated to extreme temperature exposure.

Overall, we find that the average effect of temperature exposure on the population of U.S. establishments' sales growth is zero at both the annual and quarterly frequencies. That is, we find that shocks to establishment-level temperature exposures have a statistically insignificant effect on sales. Importantly, our results in Table 2 are driven by point estimates with small economic magnitudes, and not by imprecision resulting from large standard errors. While one interpretation of our nonresults is that temperature exposures are not an important driver of establishment-level sales growth, another more nuanced story is that firm managers may respond to temperature shocks by scaling labor inputs in order to smooth output. We examine this potential channel next by analyzing how temperature exposure affects establishment-level productivity.

2.2 Do temperature exposures affect worker productivity?

Next, we examine whether temperature exposures affect worker productivity. These tests are motivated by prior literature showing that exposure to temperature extremes affects labor productivity. In particular, Graff-Zivin and Neidell (2014) study U.S. workers' time use and show that extremely hot temperatures reduce hours worked across several heat-sensitive industries. Further, 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.

We measure productivity as the ratio of sales to number of employees in a particular establishment.[11] We then replace sales with this productivity measure in the annual regression specifications outlined in Equation (1). To compute and examine variation in quarterly establishment productivity, we divide the quarterly establishment sales figures described above by the number of employees working at the establishment during the fiscal year reported by NETS.

Table 3, panel A, reports results from annual productivity regressions. In Column 1, we find that worker productivity is not significantly related to mean temperature during the year. We also do not find evidence that worker productivity is significantly related to the number of days for which temperatures exceed 30°C or fall below 0°C (Column 2). Finally, these nonresults extend to specifications where we relate worker productivity to the number of days with temperatures above the 90th or 95th percentile or days with temperatures below the 10th or 5th percentile of historical temperature distributions (Columns 3 and 4).

In panel B, we find similar results at the quarterly frequency. Worker productivity does not significantly change with mean temperature in the quarter. Worker productivity is also unrelated to extremely hot or cold days, defined using both fixed temperature cutoffs and establishment location-specific historical distributions.

Taken together, our results so far indicate that among the population of U.S. establishments in the NETS Public Database, both sales and worker productivity are not affected by temperature shocks. This finding is consistent across several temperature exposure definitions and holds at both the annual and quarterly horizons.

[11] Ideally, we would also measure total factor productivity and operating costs by establishment. However, because of NETS data limitations, we are not able to construct such measures.

Table 3
Establishment-level worker productivity regressions

	A. Annual frequency				*B. Quarterly frequency*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	0.0004				0.0002			
	(0.58)				(0.19)			
Days above 30°C		0.0000				−0.0001		
		(−0.36)				(−0.74)		
Days below 0°C		0.0000				0.0000		
		(−0.41)				(−0.17)		
Days above 90th pctl			0.0000				0.0000	
			(0.09)				(0.38)	
Days below 10th pctl			0.0000				−0.0001	
			(−0.26)				(−0.61)	
Days above 95th pctl				0.0000				0.0001
				(0.16)				(0.45)
Days below 5th pctl				0.0000				−0.0001
				(−0.42)				(−0.78)
Precipitation	0.0001	0.0001	0.0001	0.0001	−0.0005	−0.0006	−0.0005	−0.0005
	(1.21)	(0.64)	(0.88)	(0.98)	(−0.95)	(−1.14)	(−0.97)	(−0.95)
Establishment FE	Yes	Yes	Yes	Yes	No	No	No	No
Estab-calendar qtr FE	No	No	No	No	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.940	.940	.940	.940	.857	.857	.857	.857
No. observations	1,385,344	1,385,344	1,385,344	1,385,344	5,541,606	5,541,606	5,541,606	5,541,606
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. The dependent variable in all specifications is the natural log of worker productivity, which is defined as the ratio of sales to number of employees. Panel A presents estimates at the annual frequency based on Equation (1). Panel B presents estimates at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include either establishment (annual) or establishment-by-calendar-quarter (quarterly) fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the establishment and across time.

2.3 Evidence from climate-sensitive sectors

Our tests to this point indicate that abnormal temperature exposure has a minimal effect on sales and productivity for the average establishment in the continental United States. In this section, we examine whether establishments in certain sectors of the economy are especially climate sensitive. In particular, we draw on prior literature showing that extreme temperatures negatively affect labor productivity in heat-sensitive industries (Graff-Zivin and Neidell 2014), harm agricultural output (Schlenker and Roberts 2009; Fisher et al. 2012), and are associated with declines in overall output of the industrial and service sectors (Jones and Olken 2010; Hsiang 2010; Dell, Jones, and Olken 2012).

We first define an indicator for establishments that are in heat-sensitive industries. We define heat-sensitive industries as those identified by Graff-Zivin and Neidell (2014), which include the agricultural sector. Specifically, we use GICS codes to classify establishments into the Graff-Zivin and Neidell heat-sensitive industries as follows: 151050 (paper & forest products), 151040 (metals & mining), 201030 (construction & engineering), 251020 (automobile & motorcycle manufacturers), 203010 to 203050 (transportation), and 551010

Table 4
Climate-sensitive sectors

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	0.0012				0.0002			
	(0.38)				(0.26)			
× Heat-sensitive ind.	0.0000				0.0000			
	(−1.62)				(−0.28)			
Days above 30°C		0.0001				0.0000		
		(0.80)				(−0.69)		
× Heat-sensitive ind.		0.0001				0.0000		
		(0.55)				(−0.16)		
Days below 0°C		0.0000				0.0000		
		(−1.38)				(−0.62)		
× Heat-sensitive ind.		0.0005				0.0001		
		(1.91)				(0.92)		
Days above 90th pctl			0.0000				0.0000	
			(0.56)				(−0.14)	
× Heat-sensitive ind.			0.0000				0.0000	
			(−0.21)				(0.23)	
Days below 10th pctl			0.0000				0.0000	
			(−1.75)				(−0.35)	
× Heat-sensitive ind.			0.0003				0.0001	
			(1.66)				(0.64)	
Days above 95th pctl				0.0000				0.0000
				(0.17)				(−0.16)
× Heat-sensitive ind.				−0.0001				0.0000
				(−0.50)				(0.04)
Days below 5th pctl				0.0000				0.0000
				(−1.93)				(−0.42)
× Heat-sensitive ind.				0.0006				0.0001
				(2.06)				(0.91)
Precipitation	−0.0489	0.0423	−0.0016	−0.0016	0.1924	−0.0089	−0.0148	−0.0201
	(−0.08)	(1.16)	(−0.06)	(−0.05)	(1.02)	(−0.76)	(−1.35)	(−1.26)
× Heat-sensitive ind.	0.0026	0.0037	0.0034	0.0035	0.0014	0.0015	0.0014	0.0014
	(1.74)	(2.44)	(2.35)	(2.35)	(3.24)	(3.56)	(2.72)	(2.99)
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.915	.915	.915	.915	.940	.940	.940	.940
No. observations	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. Panel A presents estimates for which the dependent variable is the natural log of sales. Panel B presents estimates for which the dependent variable is the natural log of worker productivity, which is defined as the ratio of sales to number of employees. All specifications are estimated at the annual frequency based on Equation (1). Independent variables include various temperature exposure measures, defined in Section 1.2, both in levels and interacted with a heat-sensitive industry indicator. The heat-sensitive industry indicator is based on heat-sensitive industries identified by Graff-Zivin and Neidell (2014) and is equal to one for establishments with parent firms with a 6-digit GICS industry code in the following ranges: 151050 (paper & forest products), 151040 (metals & mining), 201030 (construction & engineering), 251020 (automobile & motorcycle manufacturers), 203010−203050 (transportation), 302020−302030 (food product & tobacco producers), and 551010−551050 (utilities). All regressions include establishment fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the establishment and across time.

to 551050 (utilities). Agricultural establishments are defined as those with parent companies with a 6-digit GICS code falling in the range of 302020 to 302030, which covers food product and tobacco producers.

In Table 4, panel A, we rerun our annual sales regressions from Table 2, but with interactions between the temperature exposure variables and the heat-sensitive industry dummy. For the most part, we continue to find economically and statistically insignificant estimates associated with temperature exposure. In particular, level effects of our various temperature measures remain close to zero with small magnitude t-statistics. However, two interaction terms are notable. First, the heat sensitive industry interaction with the number of days below 0°C in Column 2 loads with a t-statistic of 1.91, and indicates that among establishments in heat sensitive industries, abnormally cold days result in about a 0.05-percentage-point increase in sales. A similar result shows up when we consider the interaction effect with abnormally cold days using the 5th percentile extreme temperature cutoff in Column 4. The estimate on the interaction term indicates that abnormally cold days are associated with a 0.06-percentage-point increase in sales, and that this effect is statistically significant (t-statistic = 2.06).

In panel B, we examine the effect of the heat-sensitive industry interactions on annual establishment productivity. In contrast to our estimates for annual sales, we find no significant temperatures effects in our productivity regressions. We do, however, find statistically significant interaction effects between the heat-sensitive industry indicator and precipitation levels, though the loadings are consistently small in economic terms.

In Appendix Table A1, we find similar results at the quarterly frequency. Specifically, we find that quarterly establishment sales are generally unresponsive to temperature shocks across both heat-sensitive and non-heat-sensitive industries. This set of nonresults also carries over to our quarterly productivity regressions.

Overall, our results from establishment-level sales and productivity regressions provide very little support for our main hypotheses. In particular, we find that greater exposure to temperature extremes does not seem to affect establishment sales (*Hypothesis 1*) or productivity (*Hypothesis 2*). Furthermore, we find very little evidence that extreme temperatures differentially affect these outcomes for establishments in industries with high climate exposure (*Hypothesis 3*).

3. Firm-Level Evidence

In our next set of tests, we consider the impact of temperature exposures at firms' establishments on aggregate firm outcomes. Following our earlier analysis, we examine sales and productivity at the firm level. However, given the importance of quarterly earnings among market participants, we also examine the effect of temperature exposures on measures of firm profitability.

3.1 Firm sales and productivity

We begin by computing temperature exposure variables that are aggregated across establishments to the level of the firm. Specifically, for each firm-quarter, we take the sales-weighted average of mean temperature and precipitation levels experienced at each of the firm's establishments during the quarter. Similarly, for the absolute and relative temperature exposure variables, we compute the sales-weighted average number of days spent above or below each of the cutoffs across each firm's establishments during the quarter. We then run quarterly firm-level regressions of the form outlined in Equation (2), replacing establishment-by-calendar-quarter fixed effects with those at the firm-by-calendar-quarter level. Table 1, panel B, provides summary statistics for these variables.[12]

In Table 5, panel A, we examine the effect of temperature exposure on firm sales. As in our establishment-level specifications, we find that our temperature exposure measures are generally unimportant drivers of sales at the firm level. In particular, we find that mean temperatures exert an effect on firm sales that is statistically indistinguishable from zero (Column 1). Similarly, abnormal exposure to temperatures above 30°C and below 0°C is not associated with firm-level sales growth. However, we do find a significant effect associated with exposure to extremely cold temperatures in Columns 3 and 4. Specifically, we find that daily abnormal exposure to temperatures below the 10th (5th) percentile is associated with a positive effect on sales. Economically, the effect amounts to a 0.22- (0.28)-percentage-point increase in sales per day of abnormal cold temperature exposure. The estimated effects are also statistically significant, with respective t-statistics of 2.45 and 2.19.[13]

In Appendix Table A3, we analyze what drives the effect associated with exposure to extreme temperatures. Specifically, we fully interact the extreme temperature exposure measures with 2-digit GICS sector indicators. We find that the positive effect on sales associated with extreme cold is concentrated among firms in the Energy sector. Among Energy firms, an abnormal day of exposure to extreme cold is associated with about a 1.28- to 1.31-percentage-point increase in sales, with t-statistics of 2.66 to 2.83. This result is consistent with extreme cold driving up heating demand and leading to higher Energy sector sales. In contrast, among firms in nonenergy sectors, we find economically small and marginally significant effects (Health Care), effects that are not robust across extreme temperature cutoffs (Information Technology), or in the majority of cases, no effect associated with extreme temperature exposures.

In Table 5, panel B, we analyze the impact of temperature exposure on firm-level productivity. Echoing our earlier findings for establishments, we document

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12 We again consider an a priori analysis of the power of our firm-level tests to reject the null. In particular, we note that for our quarterly firm-level regressions with both firm-by-calendar-quarter and industry-time fixed effects, a 5% test with 90% power would require about 84,000 observations in order to detect an effect size of just 0.01 percentage points. Our baseline sample of over 160,000 observations favorably compares to this requirement and suggests that our tests do not lack sufficient power.

13 These findings also carry over to the annual frequency. See Appendix Table A2, panel A.

Table 5
Firm-level quarterly sales and productivity regressions

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0057				0.0015			
	(−0.81)				(0.71)			
Days above 30°C		0.0005				0.0002		
		(0.36)				(0.33)		
Days below 0°C		0.0014				0.0001		
		(0.89)				(0.23)		
Days above 90th pctl			0.0011				0.0006	
			(1.09)				(1.27)	
Days below 10th pctl			0.0022				0.0007	
			(2.45)				(1.59)	
Days above 95th pctl				0.0010				0.0008
				(0.68)				(1.27)
Days below 5th pctl				0.0028				0.0010
				(2.19)				(1.42)
Precipitation	−0.0077	−0.0066	−0.0052	−0.0061	0.0009	0.0010	0.0019	0.0017
	(−0.95)	(−0.78)	(−0.59)	(−0.72)	(0.31)	(0.34)	(0.60)	(0.55)
Firm-calendar qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.911	.911	.911	.911	.812	.812	.812	.812
No. observations	160,285	160,285	160,285	160,285	160,285	160,285	160,285	160,285
No. firms	4,397	4,397	4,397	4,397	4,397	4,397	4,397	4,397

This table reports firm-level regressions. The dependent variable in panel A is the natural log of firm-level sales. The dependent variable in panel B is the natural log of firm-level worker productivity, which is defined as the ratio of firm-level sales to total number of employees across a firm's establishments. All regressions are at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include firm-by-calendar-quarter fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the firm and across time.

a set of nonresults. Specifically, we find that across our measures of temperature exposure, the effects on firm productivity are estimated to be economically small and statistically insignificant. This set of findings also extends to the annual frequency (see Appendix Table A2, panel B).

3.2 Firm profitability

In Table 6, we move on to considering whether abnormal temperatures affect firm profitability. We analyze the impact of temperature on several firm-level outcomes related to quarterly profitability: operating income, net income, and earnings announcement returns.

We examine the effect of our temperature exposure variables on operating income and net income in panels A and B, respectively. Across all specifications in both panels, we continue to find a weak relationship between temperature exposure and firm-level outcomes. For example, in Column 1, we find that a 1°C increase in mean temperature leads to an average increase in operating income of just 0.02 percentage points, and that this estimate is statistically insignificant (t-statistic = 0.95). More generally, we find statistically and economically weak results for both operating income and net income across different temperature exposure variables. The lone exception is the effect of mean temperature shocks on net income in Column 5. Here, we find that a positive shock to temperature exposure is associated with increased net income, though the statistical strength of the result is only marginal (t-statistic = 1.68). Moreover, the implied economic impact of the result is rather small, with a 1°C increase in mean temperature generating only a 0.03-percentage-point increase in net income-based profitability.

In Table 6, panel C, we examine whether temperature exposures are an important predictor of the surprise component of firm profitability. As a proxy for the information content of earnings, we utilize abnormal stock returns on days surrounding earnings announcements. Specifically, we present results using abnormal returns from the [0,+3]-day window surrounding announcements (where day 0 is the announcement date), but find qualitatively identical results using announcement day returns. The estimates in panel C indicate the absence of a strong relationship between abnormal temperature exposures and subsequent earnings announcement returns. In Columns 9–12, across temperature exposure measures, the estimated coefficients are close to zero and statistically insignificant, with t-statistics ranging in magnitude from 0.04 to 1.31.

Overall, our examination of firm-level outcomes indicates that the population average effects of our temperature exposure measures are generally small in economic terms and statistically insignificant. The lone exception appears to be the positive effect of abnormal exposure to extreme cold temperatures, which we find is driven primarily by firms in the Energy sector.

Table 6
Firm-level quarterly profitability regressions

	A. Operating income				*B. Net income*				*C. Earnings announcement returns*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean temperature	0.0002				0.0003				0.0004			
	(0.95)				(1.68)				(1.31)			
Days above 30°C		0.0000				0.0001				0.0001		
		(1.20)				(1.27)				(1.07)		
Days below 0°C		0.0000				−0.0001				0.0000		
		(−0.73)				(−1.26)				(−0.28)		
Days above 90th pctl			0.0000				0.0000				0.0000	
			(0.30)				(0.46)				(0.04)	
Days below 10th pctl			0.0000				0.0000				0.0000	
			(1.28)				(0.89)				(0.07)	
Days above 95th pctl				0.0000				0.0001				0.0000
				(0.66)				(0.69)				(−0.08)
Days below 5th pctl				0.0001				0.0001				0.0000
				(1.24)				(1.36)				(−0.08)
Precipitation	−0.0002	−0.0002	−0.0002	−0.0002	0.0001	0.0001	0.0001	0.0001	−0.0000	−0.0000	−0.0000	−0.0001
	(−0.88)	(−0.76)	(−0.71)	(−0.69)	(0.18)	(0.23)	(0.28)	(0.33)	(−0.04)	(0.05)	(−0.06)	(−0.10)
Firm-calendar qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.597	.597	.597	.597	.433	.433	.433	.433	.052	.052	.052	.052
No. observations	160,285	160,285	160,285	160,285	160,285	160,285	160,285	160,285	139,098	139,098	139,098	139,098
No. firms	4,397	4,397	4,397	4,397	4,397	4,397	4,397	4,397	3,981	3,981	3,981	3,981

This table reports firm-level regressions. The dependent variable in panel A is the natural log of one plus the ratio of operating income to total assets. The dependent variable in panel B is the natural log of one plus the ratio of net income to total assets. The dependent variable in panel C is the abnormal return from the [0,+3]-day window surrounding earnings announcements, where day 0 is the announcement date. All regressions are at the quarterly frequency and are of the form outlined in Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include firm-by-calendar-quarter fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the firm and across time.

4. Robustness Checks

In our final set of tests, we examine the robustness of estimates from our baseline tests. In particular, we analyze how our results are affected by alternative standard error adjustments and by potentially heterogeneous temperature sensitivities in relatively warmer and cooler area of the United States.

4.1 Accounting for spatial correlation

In our first set of robustness tests, we rerun our baseline establishment sales regressions in Table 2 with standard errors that account for spatial correlation. In particular, we acknowledge the fact that the PRISM weather data are spatially interpolated for grid points between observed weather stations. Moreover, unobservable determinants of sales may be spatially correlated. As a result, errors are likely to be highly correlated for geographically proximate establishments, which may not be properly accounted for in the standard double-clustering approach employed in our baseline tests.

Specifically, clustering by establishment accounts for serial correlation, while clustering on the time dimension accounts for correlations across firms within a time period. However, clustering by time implicitly assumes that errors across all establishments in the United States exhibit a common correlation structure. In reality, however, errors may be more highly correlated for establishments that are geographically close to one another. Consequently, one may be concerned that double-clustering is not enough.

To address this concern, we conduct robustness checks where we account for spatial dependence in regression errors. Specifically, we implement the approach of Conley (1999). This involves an adjustment that is essentially a Bartlett window in the distance between two establishments. Within each time period, we estimate the variance-covariance matrix between two establishments in the same year based on observed errors, which are weighted by a linear distance function that is set to one for establishments that are coincident, and zero for establishments that are at least 500 miles apart. To account for autocorrelation in standard errors within establishment, we further adjust standard errors using the approach of Newey and West (1987).

Table 7 presents the results of estimating our baseline establishment sales regressions. Panel A presents estimates at the annual frequency, and panel B displays quarterly regression estimates. In both panels, to make the establishment-level estimation feasible, we focus on a random subsample of 50,000 unique establishments. This choice is driven by computational constraints associated with making the Conley adjustment. Specifically, the adjustment requires manipulation of dense error matrices with dimensions exceeding 50,000 rows and columns in some years (i.e., more than 2.5 billion nonzero elements). These calculations are computationally infeasible even for computers with multiple cores and large amounts of memory. As a result, we conduct this analysis for a random subsample of establishments that

Table 7
Establishment-level sales regressions: Standard errors adjusted for spatial correlation

	A. Annual frequency				*B. Quarterly frequency*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0031				0.0016			
	(−0.65)				(0.85)			
	(−1.08)				(1.64)			
Days above 30°C		0.0001				0.0002		
		(0.55)				(0.85)		
		(0.89)				(1.41)		
Days below 0°C		0.0004				0.0000		
		(1.42)				(−0.01)		
		(2.56)				(−0.02)		
Days above 90th pctl			0.0001				0.0002	
			(0.91)				(1.20)	
			(1.04)				(1.76)	
Days below 10th pctl			0.0000				−0.0001	
			(−0.27)				(−0.56)	
			(−0.39)				(−0.88)	
Days above 95th pctl				0.0001				0.0002
				(0.35)				(0.78)
				(0.41)				(1.08)
Days below 5th pctl				−0.0001				−0.0004
				(−0.50)				(−1.00)
				(−0.73)				(−1.54)
Precipitation	−0.0010	−0.0006	−0.0007	−0.0008	−0.0017	−0.0016	−0.0015	−0.0018
	(−1.38)	(−0.81)	(−0.84)	(−1.08)	(−1.62)	(−1.41)	(−1.46)	(−1.68)
	(−1.82)	(−1.07)	(−1.05)	(−1.38)	(−2.26)	(−2.01)	(−2.01)	(−2.32)
Establishment FE	Yes	Yes	Yes	Yes	No	No	No	No
Estab-calendar qtr FE	No	No	No	No	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.916	.916	.916	.916	.895	.895	.895	.895
No. observations	412,585	412,585	412,585	412,585	1,659,744	1,659,744	1,659,744	1,659,744
No. establishments	50,000	50,000	50,000	50,000	50,000	50,000	50,000	50,000

This table reports establishment-level regressions. The dependent variable in all specifications is the natural log of sales. Panel A presents estimates at the annual frequency based on Equation (1). Panel B presents estimates at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include either establishment (annual) or establishment-by-calendar-quarter (quarterly) fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. For comparison, we report two sets of t-statistics below coefficient estimates. The first is calculated using standard errors adjusted for clustering, both by the establishment and across time. The second is calculated using standard errors adjusted for both spatial correlation, following the method of Conley (1999), and time-series correlation using the method of Newey and West (1987).

maintains the time-series and spatial density characteristics of the overall sample. Reassuringly, we find that the estimated coefficients in Table 7 closely match up with those in our baseline tests using the full sample in Table 2.

For comparison, we present two sets of t-statistics below each coefficient estimate in Table 7. The first is calculated using standard errors adjusted for clustering, both by the firm and across time (i.e., like in Table 2). The second is calculated using standard errors adjusted for both spatial correlation, following the method of Conley (1999), and time-series correlation using the method of Newey and West (1987). Comparing t-statistics, we find that those calculated using our baseline double-clustering approach are more conservative. Across all estimated coefficients, we find that double-clustered t-statistics are of smaller magnitude than those calculated using the Conley and Newey-West adjustments. However, our empirical inferences remain largely the same, implying statistically weak effects associated with our temperature exposure measures. Overall, these results suggest that the standard double-clustering approach in our baseline results does not seem to understate standard errors.

Though we find that the Conley adjustment yields less conservative inferences in our establishment sales regressions, we have reason to believe that firm-level aggregation may generate much stronger biases related to spatial correlation. In particular, among firms with geographic footprints that are relatively spread out, establishment-level temperature exposure shocks are likely to be offset or diversified away once temperature exposure measures are aggregated to the firm level. In contrast, firms with spatially clustered establishments may be more likely to experience temperature exposure shocks that survive aggregation from establishments to the level of the firm.

To implement the firm-level Conley adjustment, we note that unlike the distance between two establishments, the distance between two firms is not well defined. For example, a hypothetical firm with two equally important establishments, one on the East Coast and the other on the West Coast, might be defined as having the same average longitude as a single-establishment firm in the middle of the United States. However, these two companies clearly should not be considered neighbors. Consequently, we proceed as follows to calculate a measure of the pairwise distances and resultant Bartlett adjustment weights between firms.[14] First, for each combination of firms during each year of the sample, we calculate a matrix of pairwise distances between each of the two firms' establishments. We then compute a linear Bartlett weighting for each pairwise distance. As in the establishment-level approach, this weight is set to one for establishments that are coincident and zero for establishments that are at least 500 miles apart. Finally, we calculate a symmetric firm-to-firm pairwise adjustment weight by taking the average of two measures.

To compute the first measure, consider two firms labeled i and j. For each of firm i's establishments, we take the Bartlett weight associated with the nearest neighboring firm j establishment. We then take the sales-weighted average of these Bartlett weights to generate a firm i-to-j weight. We repeat this process, but reversing the order of the firms, to calculate a firm j-to-i weight. Since ordering matters, we ensure symmetry by defining the weight between firms i and j to be the average of these two measures and then use this weight to account for spatial dependence using the Conley (1999) method.[15] As in the

[14] We thank an anonymous referee for both making this point and suggesting our adopted approach.

[15] An alternative approach would be to simply collapse the matrix of pairwise distances by taking sequential sales-weighted averages across establishments for both firms. However, this approach would generate very small adjustment weights for firms with geographically dispersed establishments. In particular, because of sparse weights in the establishment-to-establishment weighting matrix, the Bartlett weight for two firms with identical geographically dispersed footprints would be far less than one. In contrast, our two-stage approach that relies on nearest-neighbor weights ensures that two such firms are assigned a Bartlett weight equal to one.

Table 8
Firm-level sales regressions: Standard errors adjusted for spatial correlation

	A. Annual frequency				B. Quarterly frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0088				−0.0057			
	(−0.80)				(−0.81)			
	(−1.06)				(−1.21)			
Days above 30°C		0.0007				0.0005		
		(0.84)				(0.36)		
		(1.14)				(0.53)		
Days below 0°C		0.0011				0.0014		
		(1.23)				(0.90)		
		(1.51)				(1.28)		
Days above 90th pctl			0.0009				0.0012	
			(1.20)				(1.12)	
			(1.33)				(1.40)	
Days below 10th pctl			0.0015				0.0022	
			(2.20)				(2.45)	
			(2.42)				(2.82)	
Days above 95th pctl				0.0008				0.0010
				(0.80)				(0.70)
				(0.90)				(0.87)
Days below 5th pctl				0.0018				0.0028
				(1.84)				(2.19)
				(2.03)				(2.56)
Precipitation	−0.0032	−0.0035	−0.0015	−0.0019	−0.0077	−0.0065	−0.0051	−0.0060
	(−0.53)	(−0.57)	(−0.24)	(−0.31)	(−0.94)	(−0.77)	(−0.58)	(−0.71)
	(−0.67)	(−0.73)	(−0.30)	(−0.38)	(−1.35)	(−1.11)	(−0.84)	(−1.03)
Firm FE	Yes	Yes	Yes	Yes	No	No	No	No
Firm-calendar qtr FE	No	No	No	No	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.918	.918	.918	.918	.911	.911	.911	.911
No. observations	40,195	40,195	40,195	40,195	160,285	160,285	160,285	160,285
No. firms	4,397	4,397	4,397	4,397	4,397	4,397	4,397	4,397

This table reports firm-level regressions. The dependent variable in all specifications is the natural log of sales. Panel A presents estimates at the annual frequency based on Equation (1). Panel B presents estimates at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include either firm (annual) or firm-by-calendar-quarter (quarterly) fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes. For comparison, we report two sets of t-statistics below coefficient estimates. The first is calculated using standard errors adjusted for clustering, both by the firm and across time. The second is calculated using standard errors adjusted for both spatial correlation, following the method of Conley (1999), and time-series correlation using the method of Newey and West (1987).

establishment approach, we also adjust for time-series correlation in errors using the method of Newey and West (1987).

Table 8 presents the results of estimating our firm-level sales regressions with standard errors adjusted for spatial and time-series correlations. As before, we present two sets of t-statistics below each coefficient estimate. The first replicates the baseline firm sales results from Tables 5 and A2. The second set of t-statistics are computed using the Conley and Newey-West adjusted standard errors. As in our establishment-level comparison, we find that using standard errors that are double-clustered on the firm and time dimensions is the more conservative approach. Across all specifications at both the annual (panel A) and quarterly (panel B) frequencies, we find that our baseline test statistics are always of smaller magnitude, though both approaches yield similar inferences.

Overall, the results in this section suggest that in our setting, using the standard panel approach of double-clustered standard errors is both computationally efficient and more conservative from an inference standpoint. These results provide support for this methodological choice in our main tests throughout the paper.

4.2 Adaptation

In our next set of robustness tests, we consider the possibility that establishments in relatively hotter areas of the United States may exhibit temperature sensitivity that differs from their counterparts located in cooler parts of the country. In particular, economic agents have an incentive to adapt to local conditions. As a result, we may find differential effects associated with exposure to extreme heat and cold among establishments in locations that are generally hotter or colder.[16]

To test this conjecture, we split our sample of establishments into two subsamples based on average temperatures. Specifically, we calculate the average annual temperature experienced at each establishment location over the sample. We then define a warmer location indicator variable that equals 1 for the set of establishments in the top half of average temperatures experienced and include this variable as an interaction with each of our temperature exposure variables.

Table 9 presents the results of these tests for annual sales (panel A) and productivity (panel B). We find that for almost all temperature exposure measures, the interaction coefficients indicate no statistical difference in loadings between establishments in warmer versus cooler areas of the United States. The lone exception is in Column 1, where we find that the effect of mean temperature shocks is statistically different for establishments in warmer locations. However, the interaction effect is only marginally significant (t-statistic = 1.69), and the implied net effect for establishments in warmer locations remains statistically indistinguishable from zero.

We find similar results at the quarterly frequency in Appendix Table A4. Specifically, our estimates indicate the sales and profitability effects associated with our quarterly temperature exposure measures are generally the same for establishments located in warmer and cooler areas of the country. Further, we find the same exception as in our annual regressions, with mean temperatures being associated with a positive effect on quarterly sales growth

[16] An alternative form of adaptation would be through endogenous location choice. For example, firms might spread out their establishments geographically to benefit from spatial diversification of weather shocks. Furthermore, individual establishment locations might be selected so as to minimize the potential impact of temperature shocks. Although interesting, these considerations are beyond the scope of this study.

Table 9
Accounting for adaptation

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0021				0.0007			
	(−0.59)				(0.88)			
× Warmer location	0.0069				−0.0006			
	(1.69)				(−0.48)			
Days above 30°C		0.0000				0.0000		
		(0.33)				(−0.19)		
× Warmer location		0.0001				0.0000		
		(1.04)				(−0.09)		
Days below 0°C		0.0002				0.0000		
		(1.13)				(−1.05)		
× Warmer location		−0.0002				0.0001		
		(−1.03)				(0.99)		
Days above 90th pctl			0.0000				0.0000	
			(0.32)				(−0.17)	
× Warmer location			0.0001				0.0000	
			(0.42)				(0.23)	
Days below 10th pctl			0.0000				0.0000	
			(0.23)				(−0.41)	
× Warmer location			−0.0001				0.0000	
			(−0.72)				(0.27)	
Days above 95th pctl				−0.0001				0.0000
				(−0.37)				(−0.69)
× Warmer location				0.0002				0.0000
				(1.31)				(0.71)
Days below 5th pctl				−0.0001				−0.0001
				(−0.29)				(−1.04)
× Warmer location				−0.0001				0.0001
				(−0.20)				(0.75)
Precipitation	−0.0009	−0.0006	−0.0006	−0.0008	−0.0000	−0.0001	−0.0001	−0.0001
	(−1.37)	(−0.78)	(−0.80)	(−1.17)	(−0.16)	(−0.37)	(−0.42)	(−0.61)
× Warmer location	0.0005	0.0003	0.0002	0.0005	0.0002	0.0003	0.0003	0.0004
	(0.69)	(0.37)	(0.19)	(0.55)	(0.79)	(0.85)	(0.95)	(1.16)
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.915	.915	.915	.915	.940	.940	.940	.940
No. observations	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344	1,385,344
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. Panel A presents estimates for which the dependent variable is the natural log of sales. Panel B presents estimates for which the dependent variable is the natural log of worker productivity, which is defined as the ratio of sales to number of employees. All specifications are estimated at the annual frequency based on Equation (1). Independent variables include various temperature exposure measures, defined in Section 1.2, both in levels and interacted with a warmer location indicator. The warmer location indicator is equal to one if the average temperature experienced at an establishment location over the sample is above the median across all establishments. All regressions include establishment fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics reported below coefficient estimates are calculated using standard errors adjusted for clustering, both by the establishment and across time.

for establishments in warmer locations. Overall, our tests provide limited evidence in support of an adaptation story whereby establishments in relatively different climate regions of the United States react differently to temperature exposure shocks.

5. Discussion and Concluding Remarks

In this paper, we study how exposure to temperature shocks affects establishment sales and productivity. Motivated by climate scientists' projections of a continuing rise in both average temperatures and the frequency of temperature extremes, we build a panel of establishment-level temperature exposures. At both the annual and quarterly frequencies, we find that the effects of temperature shocks are economically small and statistically insignificant, including among industries identified as heat sensitive in prior literature. We find similar nonresults at the firm level, where we document that temperature exposures aggregated across firm establishments are generally unrelated to sales, productivity, and earnings.

Though we document a consistent set of nonresults, our tests provide a starting point for further examination. For example, while we find population average treatment effects that are close to zero, certain sectors of the U.S. economy may be more vulnerable to temperature shocks. Furthermore, sector-specific sensitivities also may be time dependent, showing up only during certain months or seasons. Finally, to the extent that such sensitivities exist, another important line of inquiry would be to ask whether key market participants, such as analysts and investors, understand these relationships. We leave these important questions for future research.

Appendix

Table A1
Climate-sensitive sectors, quarterly frequency

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	0.0012				0.0003			
	(0.71)				(0.31)			
× Heat-sensitive ind.	0.0000				0.0000			
	(−1.91)				(−1.18)			
Days above 30°C		0.0001				−0.0001		
		(0.41)				(−0.77)		
× Heat-sensitive ind.		0.0000				0.0000		
		(−0.06)				(−0.32)		
Days below 0°C		0.0000				0.0000		
		(−1.81)				(−1.39)		
× Heat-sensitive ind.		0.0005				0.0001		
		(1.30)				(0.51)		
Days above 90th pctl			0.0002				0.0000	
			(0.88)				(0.42)	
× Heat-sensitive ind.			−0.0001				−0.0001	
			(−0.58)				(−0.47)	
Days below 10th pctl			0.0000				0.0000	
			(−1.84)				(−1.19)	
× Heat-sensitive ind.			0.0003				−0.0001	
			(0.87)				(−0.33)	
Days above 95th pctl				0.0002				0.0001
				(0.63)				(0.40)
× Heat-sensitive ind.				−0.0003				−0.0001
				(−0.88)				(−0.70)
Days below 5th pctl				0.0000				0.0000
				(−1.94)				(−1.19)
× Heat-sensitive ind.				0.0006				0.0000
				(1.32)				(0.05)
Precipitation	−0.2785	0.0892	0.0077	0.0234	−0.1236	0.0253	−0.0094	−0.0004
	(−1.04)	(1.93)	(0.19)	(0.43)	(−0.86)	(1.03)	(−0.41)	(−0.01)
× Heat-sensitive ind.	0.0031	0.0043	0.0039	0.0041	0.0016	0.0020	0.0016	0.0018
	(1.87)	(2.57)	(2.27)	(2.36)	(2.17)	(2.42)	(1.97)	(2.15)
Estab-calendar qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.895	.895	.895	.895	.857	.857	.857	.857
No. observations	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. Panel A presents estimates for which the dependent variable is the natural log of sales. Panel B presents estimates for which the dependent variable is the natural log of worker productivity, which is defined as the ratio of sales to number of employees. All specifications are estimated at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2, both in levels and interacted with a heat-sensitive industry indicator. The heat-sensitive industry indicator is based on heat-sensitive industries identified by Graff-Zivin and Neidell (2014) and is equal to one for establishments with parent firms with a 6-digit GICS industry code in the following ranges: 151050 (paper & forest products), 151040 (metals & mining), 201030 (construction & engineering), 251020 (automobile & motorcycle manufacturers), 203010−203050 (transportation), 302020−302030 (food product & tobacco producers), and 551010−551050 (utilities). All regressions include establishment-by-calendar-quarter fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics reported below coefficient estimates are calculated using standard errors adjusted for clustering, both by the establishment and across time.

Table A2
Firm-level annual sales and productivity regressions

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0088				0.0016			
	(−0.80)				(0.49)			
Days above 30°C		0.0007				0.0001		
		(0.84)				(0.32)		
Days below 0°C		0.0011				0.0000		
		(1.23)				(0.01)		
Days above 90th pctl			0.0009				0.0000	
			(1.20)				(0.02)	
Days below 10th pctl			0.0015				0.0000	
			(2.20)				(0.07)	
Days above 95th pctl				0.0008				0.0002
				(0.80)				(0.36)
Days below 5th pctl				0.0018				0.0000
				(1.84)				(−0.03)
Precipitation	−0.0032	−0.0035	−0.0015	−0.0019	0.0014	0.0014	0.0014	0.00015
	(−0.53)	(−0.57)	(−0.24)	(−0.31)	(0.68)	(0.69)	(0.61)	(0.68)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.918	.918	.918	.918	.863	.863	.863	.863
No. observations	40,195	40,195	40,195	40,195	40,195	40,195	40,195	40,195
No. firms	4,397	4,397	4,397	4,397	4,397	4,397	4,397	4,397

This table reports firm-level regressions. The dependent variable in panel A is the natural log of firm-level sales. The dependent variable in panel B is the natural log of firm-level worker productivity, which is defined as the ratio of firm-level sales to total number of employees across a firm's establishments. All regressions are at the annual frequency based on Equation (1). Independent variables include various temperature exposure measures, defined in Section 1.2. All regressions include firm fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the firm and across time.

Table A3
Firm-level quarterly sales regressions, GICS sector interactions

	Sales	
	(1) Extreme 10%	(2) Extreme 5%
Days above extreme pctl ×		
GICS sector 10 (Energy)	0.0068	0.0070
	(1.62)	(1.24)
GICS sector 15 (Materials)	0.0024	0.0041
	(0.75)	(0.98)
GICS sector 20 (Industrials)	0.0033	0.0062
	(1.26)	(1.66)
GICS sector 25 (Consumer Discretionary)	−0.0014	−0.0030
	(−0.55)	(−0.81)
GICS sector 30 (Consumer Staples)	0.0019	0.0013
	(0.88)	(0.42)
GICS sector 35 (Health Care)	0.0014	0.0005
	(0.62)	(0.18)
GICS sector 40 (Financials)	0.0011	0.0018
	(0.29)	(0.35)
GICS sector 45 (Information Technology)	0.0004	0.0006
	(0.18)	(0.17)
GICS sector 50 (Communication Services)	−0.0061	−0.0098
	(−0.75)	(−0.94)
GICS sector 55 (Utilities)	−0.0010	−0.0042
	(−0.27)	(−0.81)
GICS sector 60 (Real Estate)	0.0032	0.0030
	(0.35)	(0.22)
Days below extreme pctl ×		
GICS sector 10 (Energy)	0.0128	0.0131
	(2.66)	(2.83)
GICS sector 15 (Materials)	−0.0056	−0.0068
	(−1.45)	(−1.26)
GICS sector 20 (Industrials)	0.0019	0.0011
	(0.83)	(0.33)
GICS sector 25 (Consumer Discretionary)	0.0002	0.0006
	(0.08)	(0.20)
GICS sector 30 (Consumer Staples)	0.0017	0.0027
	(0.55)	(0.66)
GICS sector 35 (Health Care)	0.0036	0.0047
	(1.67)	(1.70)
GICS sector 40 (Financials)	−0.0026	−0.0035
	(−0.74)	(−0.71)
GICS sector 45 (Information Technology)	0.0027	0.0047
	(1.47)	(1.90)
GICS sector 50 (Communication Services)	−0.0008	0.0000
	(−0.11)	(0.01)
GICS sector 55 (Utilities)	0.0011	0.0007
	(0.28)	(0.15)
GICS sector 60 (Real Estate)	0.0147	0.0185
	(1.34)	(1.05)
Firm-calendar qtr FE	Yes	Yes
Time-industry FE	Yes	Yes
Adj. R^2	.911	.911
No. observations	160,285	160,285
No. firms	4,397	4,397

This table reports firm-level regressions where the dependent variable is the natural log of sales. All specifications are estimated at the quarterly frequency based on Equation (2). In Column 1, the independent variables are temperature exposure measures based on the number of days spent past the extreme 10% tails of the historical temperature distribution (see Section 1.2) fully interacted with 11 GICS sector indicators. In Column 2, the temperature exposure measures are based on the number of days spent past the extreme 5% tails of the historical temperature distribution. In both columns, precipitation is also fully interacted with the sector indicators, but coefficients are suppressed for brevity. All regressions include firm-by-calendar-quarter fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the firm and across time.

Table A4
Accounting for adaptation, quarterly frequency

	A. Sales				*B. Productivity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean temperature	−0.0003				0.0000			
	(−0.22)				(0.06)			
× Warmer location	0.0030				0.0003			
	(2.04)				(0.49)			
Days above 30°C		−0.0001				−0.0001		
		(−0.24)				(−0.71)		
× Warmer location		0.0003				0.0000		
		(1.16)				(0.26)		
Days below 0°C		0.0002				0.0000		
		(0.65)				(−0.18)		
× Warmer location		−0.0003				0.0000		
		(−1.13)				(0.11)		
Days above 90th pctl			0.0001				0.0000	
			(0.32)				(0.13)	
× Warmer location			0.0002				0.0000	
			(0.69)				(0.21)	
Days below 10th pctl			−0.0001				−0.0001	
			(−0.42)				(−1.20)	
× Warmer location			0.0000				0.0001	
			(−0.19)				(0.71)	
Days above 95th pctl				0.0000				0.0000
				(−0.07)				(0.19)
× Warmer location				0.0004				0.0000
				(1.13)				(0.21)
Days below 5th pctl				−0.0003				−0.0002
				(−0.72)				(−1.27)
× Warmer location				0.0000				0.0001
				(−0.11)				(0.60)
Precipitation	−0.0007	−0.0007	−0.0006	−0.0007	−0.0001	−0.0002	−0.0001	−0.0001
	(−0.77)	(−0.73)	(−0.63)	(−0.80)	(−0.16)	(−0.42)	(−0.22)	(−0.20)
× Warmer location	−0.0010	−0.0010	−0.0011	−0.0010	−0.0006	−0.0006	−0.0006	−0.0006
	(−0.97)	(−0.93)	(−1.06)	(−1.00)	(−1.04)	(−0.97)	(−0.93)	(−1.02)
Estab-calendar qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	.895	.895	.895	.895	.857	.857	.857	.857
No. observations	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606	5,541,606
No. establishments	167,623	167,623	167,623	167,623	167,623	167,623	167,623	167,623

This table reports establishment-level regressions. Panel A presents estimates for which the dependent variable is the natural log of sales. Panel B presents estimates for which the dependent variable is the natural log of worker productivity, which is defined as the ratio of sales to number of employees. All specifications are estimated at the quarterly frequency based on Equation (2). Independent variables include various temperature exposure measures, defined in Section 1.2, both in levels and interacted with a warmer location indicator. The warmer location indicator is equal to one if the average temperature experienced at an establishment location over the sample is above the median across all establishments. All regressions include establishment-by-calendar-quarter fixed effects and industry-time fixed effects, where industries are defined using 6-digit GICS codes of the parent firm. t-statistics, reported below coefficient estimates, are calculated using standard errors adjusted for clustering, both by the establishment and across time.

References

Alfaro, L., and M. X. Chen. 2012. Surviving the global financial crisis: Foreign ownership and establishment performance. *American Economic Journal: Economic Policy* 4:30–55.

Bansal, R., D. Kiku, and M. Ochoa. 2016a. Climate change and growth risks. Working Paper, Duke University.

———. 2016b. Price of long-run temperature shifts in capital markets. Working Paper, Duke University.

Blanc, E., and W. Schlenker. 2017, The use of panel models in assessments of climate impacts on agriculture. *Review of Environmental Economics and Policy* 11:258–79.

Burke, M., S. M. Hsiang, and E. Miguel. 2015. Global non-linear effect of temperature on economic production. Nature 527:235–39.

Conley, T. G. 1999. GMM estimation with cross sectional dependence. *Journal of Econometrics* 92:1–45.

Dell, M., B. F. Jones, and B. A Olken. 2009. Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review* 99:198–204.

———. 2012. Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics* 4:66–95.

———. 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature* 52:740–98.

Deschênes, O., and M. Greenstone. 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics* 3:152–85.

Fisher, A. C., W. M. Hanemann, M. J. Roberts, and W. Schlenker. 2012. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment. *American Economic Review* 102:3749–60.

Gallup, J. Luke, J. D. Sachs, and A. D. Mellinger. 1999. Geography and economic development. *International Regional Science Review* 22:179–232.

Giroud, X. 2013. Proximity and investment: Evidence from plant-level data. *Quarterly Journal of Economics* 128:861–915.

Graff-Zivin, J., and M. Neidell. 2012. The impact of pollution on worker productivity. *American Economic Review* 102:3652–73.

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

Hong, H. G., F. W. Li, and J. Xu. 2017. Climate risks and market efficiency. *Journal of Econometrics* 208:265–81.

Howe, P. D., M. Mildenberger, J. R. Marlon, and A. Leiserowitz. 2015. Geographic variation in opinions on climate change at state and local scales in the USA. *Nature Climate Change* 5:596–603.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, et al. 2017. Estimating economic damage from climate change in the United States. *Science* 356:1362–9.

Hsiang, S. M. 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences* 107:15367–72.

Huntington, E. 1915. *Climate and civilization*. New York: Harper & Bros.

IPCC. 2014. AR5 Synthesis report: Climate change 2014. Contribution of working groups i, ii, and iii to the fifth assessment report of the intergovernmental panel on climate change. Report, IPCC, Geneva, Switzerland.

Jones, B. F., and B. A. Olken. 2010. Climate shocks and exports. *American Economic Review* 100:454–9.

Lau, N.-C., and M. J. Nath. 2012. A model study of heat waves over North America: Meteorological aspects and projections for the twenty-first century. *Journal of Climate* 25:4761–84.

Midrigan, V., and D. Y. Xu. 2014. Finance and misallocation: Evidence from plant-level data. *American Economic Review* 104:422–58.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–8.

Ortiz-Bobea, A., E. Knippenberg, and R. G. Chambers. 2018. Growing climatic sensitivity of US agriculture linked to technological change and regional specialization. *Science Advances* 4, eaat4343.

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

Schlenker, W., and M. J. Roberts. 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences* 106:15594–8.

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