Temperature, Adaptation, and Local Industry Concentration*

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Abstract

We use plant-level data from the U.S. Census of Manufacturers to study the short- and long-run effects of temperature on manufacturing activity. In the short-run, high-temperature shocks significantly increase energy costs and lower productivity for small plants, while large plants are mostly unaffected. In the long-run, commuting zones with higher increases in temperatures between the 1980s and the 2010s experience a decline in the number of plants and higher local labor market concentration. Differences in costs per unit of energy, managerial skills, and – to a more limited extent – hedging across locations contribute to explaining why large firms are better able to adapt to climate change.

Keywords: Climate Change, U.S. Manufacturing, Plant-level data, electricity costs, productivity

JEL Classification: Q54, O14, G3, L11

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I Introduction

Average global temperatures increased substantially over the 20th century and will continue to rise (IPCC, 2021). In the continental United States, the pace of warming started accelerating in the 1980s, with a county-level median increase in temperatures of 0.6°C from the 1980s to the 2010s and nine in ten counties experiencing higher average temperatures over that period. Even under optimistic climate mitigation scenarios, the average county-level number of days with maximum temperature above 30°C is expected to increase from 60 days in the 2010s to about 90 days by the end of the 21st century, representing a approximately 50% increase. Under worst-case scenarios, this number is expected to increase by approximately 150%.[1] These facts and projections have put the effects of a warming climate on socioeconomic outcomes at the center of political and academic debates.

We contribute to this debate by providing new micro-based evidence on the short- and long-run effects of temperature on U.S. manufacturing plants. The manufacturing sector is both economically important (11% of U.S. GDP in 2022 according to the U.S. Bureau of Economic Analysis) and characterized by large heterogeneity in plant characteristics, leading to considerable variation in scope for adaptation. To the extent that some manufacturing plants are better able to adapt to higher temperatures, such as through investments in energy-efficient machinery, better insulated buildings, or temperature control systems, manufacturing activity may reallocate towards such plants, leading to a higher concentration in local labor markets.

We employ four decades of plant-level data from the U.S. Census Bureau (starting in 1980), as well as detailed weather data for the contiguous U.S. Three features of the Census data make them particularly suitable to address the challenges associated with studying responses to temperature shocks. First, the availability of detailed establishment-level characteristics, such as energy costs and productivity, allows a comprehensive examination of the impact of temperature shocks on manufacturing activity. Second, the ability to observe the cross-section of plants allows us to study the heterogeneous effects of temperature shocks across establishments of different sizes. Third, observing annual plant performance over four decades enables us to study how manufacturing activity responds to long-run temperature changes.

We combine the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM) to measure plants' energy costs, productivity, and size, and use the Longitudinal Business Database (LBD), an administrative register that tracks all business

[1] Statistics on past temperature trends are calculated based on PRISM Climate Group temperature data (cleaned and made available by Wolfram Schlenker at `http://www.columbia.edu/~ws2162/links.html`). Expectations for climate change over the remainder of the 21st century are derived from data generated by Hsiang et al. (2017). See Section II.B for further details. As is common practice, we use the term weather to refer to realizations of temperature, drawn from an underlying distribution, and climate to refer to moments of the weather distribution (e.g., Auffhammer (2018), Dell et al. (2012)).

establishments in the US, to identify plant entry and exit in different geographic locations.

In order to estimate the effect of temperature on manufacturing plants, we employ two empirical strategies used in climate economics (e.g., Burke and Emerick 2016, Heutel et al. 2021). The first strategy captures the contemporaneous response of manufacturing outcomes to additional high-temperature days. This allows us to quantify the effect of additional days in certain temperature bins in a given year on plant-level outcomes such as energy costs and productivity. The second strategy captures the long-term response of manufacturing activity (e.g., entry, exit, and concentration) to changes in average climate experienced by U.S. commuting zones (CZs) over the last four decades.

We start by estimating a panel regression at the plant-year level, which exploits yearly variation in temperature in the ZIP Code where the plant is located. We think of these yearly temperature shocks as random weather draws from the climate distribution in a given geographical area, and therefore as plausibly exogenous to the outcomes of interest (Dell et al., 2014). Because of our focus on manufacturing, we view each U.S. ZIP code or CZ as a small open economy and manufacturing as a tradable sector whose demand is geographically sparse across the U.S. and the rest of the world, and thus relatively independent from local demand shocks. Under this assumption, temperature shocks are likely to identify supply forces, such as higher input costs or negative labor productivity shocks, rather than any effect of temperature on local demand of the goods produced by each plant.

Two key findings emerge from our estimates of the short-run effects of temperature shocks on manufacturing outcomes. First, the input costs associated with temperature management (expenditures in electricity and fuel) and productivity react to contemporaneous temperature shocks. In particular, a higher-than-usual number of hot days results in higher energy costs and lower plant productivity. Second, these effects are significantly stronger in small manufacturing plants, while large establishments are mostly unaffected.

Despite these contemporaneous negative effects on small plants, we observe no significant contemporaneous response of small plants via down-scaling (as measured by employment) or via exiting a given location. Indeed, it is plausible that key industrial decisions, such as scaling back on the size of a plant or exiting a given market, are not driven by abnormal weather shocks during the year, especially if such shocks are interpreted as idiosyncratic and therefore likely to revert to normal in the following years.

We show that our results are robust to a set of additional tests designed to investigate potential identification concerns. In particular, temperature shocks might affect local demand in less tradable manufacturing sectors, or might affect manufacturing production via input-output linkages with local agriculture. To deal with these concerns, we show that our results are quantitatively similar when focusing on manufacturing sectors with high levels of tradability, or when excluding manufacturing sectors whose production strongly relies on inputs from agriculture.

Next, we move to a long-run approach to study how manufacturing activity in a geographic area responds to the cumulative effect of several years of warmer than usual weather via the intensive and extensive margins. The rationale of this analysis is that a series of deviations from past average temperatures might indicate a shift in the climate distribution that warrants an adaptive response by local plants. For this analysis we use a long differences approach as in Burke and Emerick (2016). In particular, we estimate a U.S. CZ-level regression relating long-run changes in manufacturing activity to long-run changes in average temperatures between the 1980s and the 2010s, controlling for division-specific common trends and for differential trends across CZs with different initial observable characteristics.

We find that, over the last four decades, areas where the climate got warmer at a faster pace experienced larger declines in the number of plants but no differential change in total employment, consistent with a reallocation of employment from small to large plants. Indeed, we also document that higher average temperatures increased concentration of manufacturing activity among the largest plants at the CZ-industry level. The estimates indicate that industries in areas that, between the 1980s and the 2010s, experienced a one standard deviation higher increase in temperatures (about 90 cooling degree days (CDDs) above 18°C per year) saw a 0.5 percentage points larger increase in the share of employment concentrated in the top 4 largest plants and a 3% larger increase in the Herfindahl-Hirschman Index (HHI).[2]

These findings suggest that large manufacturing plants might be better equipped for long-run adaptation to climate change than small ones. We test potential mechanisms that may rationalize this result.

First, survey data from the Manufacturing Energy Consumption Survey (MECS) shows that large plants face lower prices per unit of energy. This could partly attenuate the adverse impact of higher temperatures on large plants. To test this mechanism, we interact long-run changes in temperature at the CZ level with dummy capturing above-median electricity prices (dollars per unit of energy) sourced from MECS. We document that the effect of higher temperatures on concentration is significantly larger for industry-regions facing higher energy costs, consistent with energy prices being a potential transmission mechanism linking warming temperatures with industry concentration over the long run.

Second, and related to the first mechanism, large plants may be run by better trained managers who can both understand the change in exposure to climate risk and proactively invest in adaptation, including investment in energy-efficient machinery and equipment. We test this mechanism by exploiting data on participation in electricity management practices sourced from the MECS. Consistent with this mechanism, we find that higher

[2] A daily Cooling Degree Day (CDD) is the difference in degrees between maximum daily temperature and 18°C conditional on the maximum daily temperature being above 18°C, see Heutel et al. (2021) or Zivin and Kahn (2016). Yearly CDD is the sum of all daily CDDs in a given year.

participation rates in electricity management practices leads to a lower impact of long-run changes in temperatures on industry concentration.

Third, large plants may have better access to external finance, which allows them to cope with weather shocks, reducing the need to downscale employment or close plants. To test this mechanism, we exploit variation in the density of bank branches per capita across CZs as a proxy for local financial development and ability to access bank financing for small and medium plants. Estimates are too noisy to draw strong conclusions on the role of this mechanism.

Finally, existing literature has shown that multi-plant firms may be naturally better hedged to absorb weather shocks, even when shocks occur at higher frequency due to climate change, because multi-plant firms produce output across different locations, allowing them to diversify climate risk (Castro-Vincenzi, 2022; Acharya et al., 2023). This mechanism could help rationalize the long run effects of temperature on labor market concentration into large plants, because large plants are more likely than small plants to be part of a multi-unit firm. We document that some of the effects of long-run changes in temperature on industry concentration are smaller in areas where a larger share of local small plants are part of a multi-unit firm.

Related Literature

A large literature in economics has studied the relation between climate change and macroeconomic outcomes (see Dell et al. 2014 for a comprehensive list of outcomes studied and methods employed in the literature). Previous studies on country-level output and productivity have mostly focused on documenting the adverse effects of weather shocks and climate change in developing economies, which tend to be on average more exposed to such shocks due to their geography and the large share of agriculture in their economies (Burke et al. 2015, Chen and Yang 2019, Colacito et al. 2019, Dell et al. 2009, Dell et al. 2012, Gallup et al. 1999, Hsiang 2010, Jones and Olken 2010).[3]

Our work is further related to several recent papers studying the effect of temperature on firm outcomes. Addoum et al. (2021) show that higher temperatures affect the profitability of U.S. public firms across more than 40% of industries, and Acharya et al. (2022) show that higher temperatures lead to higher bond yields and expected returns for equity. Addoum et al. (2020) document that higher temperatures do not significantly affect the sales and productivity of establishments owned by U.S. public firms.[4] Our contribution to

[3]A notable exception to the focus on developing nations are studies of the agricultural sector in developed economies. Here, short-term temperature shocks are generally found to have adverse implications for productivity once nonlinearities are considered. See, for instance, Burke and Emerick (2016), Fisher et al. (2012), Ortiz-Bobea et al. (2018), Schlenker and Roberts (2009) for evidence on the U.S., Lobell et al. (2011) for global evidence, Gupta et al. (2017) and Auffhammer et al. (2006) for evidence on India. In addition, Deryugina and Hsiang (2014) show that temperature affects income even in the U.S.

[4]For international evidence, Zhang et al. (2018) show that Chinese manufacturing firms exhibit an inverted U-shape relation between temperature and total factor productivity, consistent with macro-level evidence for developing countries. Focusing on Italian firms, Caggese et al. (2023) present a general equi-

this literature is to use micro-data representative of U.S. manufacturing plants of all sizes, including small standalone plants, to document how, even in a developed economy, small plants are negatively affected by temperature shocks via energy costs and productivity. The key novel finding is that small establishments are disproportionately more affected by a warming climate, which–over the last four decades–has led to higher concentration in local labor markets.

Our results are also informative for the literature on adaptation, especially the notion that productive firms, which also contribute more to overall industry productivity, have greater incentives to adapt (Zivin and Kahn 2016, Somanathan et al. 2021; see Samuelson 1947 and Viner 1958 for the theoretical foundations). Clients with multiple suppliers, for instance, dynamically adjust their supplier network in response to weather shocks (Custodio et al. 2022, Pankratz and Schiller 2021). Further, heat waves result in geographic production reallocation to unaffected locations among firms with multi-location operations and downsizing by standalone firms (Castro-Vincenzi 2022, Acharya et al. 2023), while firms that employ outdoor workers substitute capital for labor in response to temperature extremes and heat-related regulation (Xiao 2022).

Finally, our findings are informative for the large literature on industry concentration. Drivers behind the increase in industry concentration observed in the U.S. over the last decades (De Loecker et al. 2020, Grullon et al. 2019, Covarrubias et al. 2020, Kwon et al. 2023) are broadly of technological or political nature, with work focusing on channels such as the efficient scale of operation (Autor et al. 2017, Autor et al. 2020), the decrease in domestic competition (Gutiérrez and Philippon 2017), and the increasing importance of globalization (Feenstra and Weinstein 2017), as well as the shift away from physical to intangible capital (Alexander and Eberly 2018, Crouzet and Eberly 2021). We contribute to this literature by documenting that climate change, through its adverse impact on small firms, is an additional key driver contributing to increased local industry concentration. We further explore potential mechanisms, including differential energy costs, managerial skills, and access to finance.

The rest of the paper is organized as follows. In Section II, we describe the data and offer some background information on the changes in average temperatures in the continental U.S. in recent decades. In Section III, we present the identification strategy. In Section IV, we discuss the results and in Section IV.C, we discuss the mechanisms that can be employed to rationalize our findings.

librium structural framework to separate the effects of temperature on firm-level demand, productivity, and input misallocation to examine the aggregate productivity losses caused by climate change. LoPalo (2023) examines the productivity of interviewers across 46 countries and finds that interviewers complete fewer interviews per hour on the hottest and most humid days.

II Data and Background

Key to our analysis of the short- and long-run effects of temperature on U.S. manufacturing plants are data on U.S. manufacturing plants and detailed temperature data. We describe each in turn and then provide an overview of temperature trends in the U.S.

II.A Data

Manufacturing Establishments. To measure manufacturing activity, we rely on three complementary establishment-level data sets from the U.S. Census Bureau. First, we employ the Longitudinal Business Database (LBD), an administrative register that tracks all business establishments. The LBD provides information on establishment geographic locations and industry classification. We employ data on the number of employees to distinguish the establishment size. We have access to LBD data for the 1977 to 2019 period.

Second, we combine data on the activities of manufacturing establishments from the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM). Manufacturing establishments are those with 2-digit NAICS code 31, 32 or 33. The CMF covers all U.S. manufacturing plants with at least one employee and it is carried out every five years. The ASM provides data on non-Census years for a sample of 50,000 to 70,000 manufacturing establishments, including all establishments with more than 250 employees and a representative sample of smaller establishments. Sampling weights are reported for all plant-years to reflect that smaller manufacturing establishments are less likely to be surveyed relative to their large peers.[5] We construct a panel at the plant-year level in which we use plants covered by the ASM in non-Census years, and CMF plants that are also observed in the ASM in Census years. The ASM/CMF data span from 1973 to 2018. These two datasets provide detailed industry classification, business group affiliation, output (measured by value of shipments), energy costs, total working hours, and employment for our analysis. We also use total factor productivity (TFP) as in Foster et al. (2016) (see their Appendix). A mandatory reporting requirement and fines for misreporting help to ensure the quality of the data.

Weather Data. We use two data sources to capture the weather and temperature-related changes in climate, as well as other climate shocks, respectively. Weather data for the contiguous U.S. over the 1950-2019 period is provided by the PRISM Climate Group. We rely on the cleaned version provided on Wolfram Schlenker's homepage.[6] The data include the daily minimum and maximum temperatures for 2.5-mile by 2.5-mile grids on the basis

[5] See Foster et al. (2016) and Ersahin et al. (2021) for further details.

[6] For details such as treatment of missing values and selection of underlying stations, please refer to: `http://www.columbia.edu/~ws2162/links.html`.

of a constant set of weather stations that receive a constant weight over the 1950-2019 sample period. This treatment ensures that the resulting time series of temperatures does not vary through the birth and death of stations or missing observations (see Auffhammer et al. (2013) for a discussion).

For our plant-level analysis, we measure plants' temperature exposure at the ZIP Code level. In order to obtain ZIP Code-level maximum daily temperatures, we calculate the value-weighted daily maximum temperature using grid points within a 20-mile radius of the ZIP Code centroid and their inverse distance to the centroid as the weight, following Heutel et al. (2021). For our CZ-level analysis, we weight all grid-level temperature observations within a commuting zone by their inverse distance to the geographic CZ midpoint. We obtain and process daily precipitation information using the same method. On the basis of the resulting respective ZIP Code-day and CZ-day temperature time series, we construct various aggregate yearly temperature measures of interest, such as number of days within certain temperature bins, as well as Cooling Degree Days ($CDDs$) and Heating Degree Days ($HDDs$).

We also obtain data on extreme weather events, such as droughts and floods, heatwaves and winter weather, as well as hurricanes and tornadoes from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[7] SHELDUS covers the 1960 to 2021 period and assigns events to CZs; underlying data are from the National Center for Environmental Information and SHELDUS has significantly more records of natural disaster events than alternative data provided by alternative data sources, such as the Federal Emergency Management Agency (FEMA). We use hazards reported by SHELDUS as controls and also to validate our temperature data.

Economic and Demographic Controls. Socioeconomic and demographic controls at the CZ level are based on the 1980 Census and serve as controls for pre-sample period conditions. Income per capita and population are obtained directly from the Census webpage, and the fraction of the population above 25 years of age with a college degree is imputed from data provided through IPUMS-NGHIS (the National Historical Geographic Information System). Another control captures the change in exposure to import competition from China over the 1990 to 2007 period and reflects exposure per worker as in Autor et al. (2013) on the basis of UN Comtrade data. Mechanism tests also rely on data on electricity prices and participation in electricity management practices from the Manufacturing Energy Consumption Survey (MECS), as well as data on bank branches from the Federal Deposit Insurance Corporation (FDIC). Table A.1 reports the definition and data source for all variables used in the empirical analysis.

[7] ASU Center for Emergency Management and Homeland Security (2023). The Spatial Hazard Events and Losses Database for the United States, Version 21.0 [Online Database]. Phoenix, Arizona: Arizona State University. Available from `https://cemhs.asu.edu/sheldus`.

II.B Background on temperature changes in the U.S.

The contiguous U.S. has experienced substantial increases in average temperature over the 20th century. According to the climatology literature described in the IPCC (2021) report, the significant emergence of changes in temperature relative to historical averages occurred in North America after 1981.[8] Figure 1 shows the dynamics of annual average surface temperature anomalies across the contiguous 48 states over the 1900 to 1920 period. A temperature anomaly is the difference between the average annual temperature and the average temperature over the 1901 to 2000 period. Figure 1 shows that after mild increases in average temperature in the 1930s and 1940s, the 1960s and 1970s witnessed a cooling period. In line with the IPCC (2021) report, average temperatures increased rapidly and consistently after 1980. This trend is particularly pronounced in the 2000s and 2010s, and the 2012 to 2016 period experienced some of the highest abnormal temperatures over the last 120 years.

Average temperatures are predicted to continue to increase for the next decades, as shown by long-run projections of temperatures in the U.S. for the remainder of the 21st century. In Figure A.1, we illustrate these long-run predictions using data by Hsiang et al. (2017). These data contain binned projections of daily weather (1981-2100) for U.S. counties using 44 different climate models. We record the number of days that fall within 1°C bins within a year (from -20°C to 40°C).[9] Next, we take the average days across all climate models for each county-year, and then calculate the mean value across all counties in a decade.

Climate modeling generally considers four Representative Concentration Pathways (RCPs) to describe different 21st-century pathways of greenhouse gas (GHG) emissions and atmospheric concentrations. The RCPs include a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high GHG emissions (RCP8.5, frequently referred to as "business as usual" or "worst-case scenario"). The most pronounced pattern in Figure A.1 is the sharp spikes in the number of extremely hot days, namely days with a maximum temperature equal or above 30°C. The average number of days in this temperature bin increases from about 60 days in the 2010s to 85 days by the end of the 21st century under the optimistic scenario (RCP2.6), 100 days under the intermediate scenario (RCP4.5), and about 140 days under the worst-case scenario (RCP8.5).

Figure A.2 illustrates the geographic distribution in the U.S. of projected changes in extremely hot days between the 1980s and the 2090s. Across all three RCPs, we observe a prevalent increase in the number of extremely hot days, with the largest increases

[8] See IPCC (2021), p. 133. Historical climate averages are calculated using temperature data for the baseline period from 1850 to 1900.

[9] In order to align the arguments in this section with our later analysis, we group temperature projections into coarser bins of 3°C. In particular, we create 9 bins of 3°C each, ranging from 3°C to 29°C, plus two additional bins capturing average daily temperatures below 3°C and above 29°C.

predicted to occur in counties in southern and central states. Notably, there is also significant variation in projected hot days across counties within each state.

III Empirical Strategy

We employ two approaches to estimate the effect of temperature on manufacturing outcomes. Our first approach – the panel approach – is designed to capture the contemporaneous response of manufacturing outcomes to short-term (yearly) temperature shocks. Our second approach – the long differences approach – captures the long-term response of manufacturing activity to changes in the temperature experienced by a U.S. CZ over four decades (from the 1980s to the 2010s).[10]

III.A Panel approach to study the short-run effects of temperature

We examine the short-run effects of temperature on manufacturing outcomes by estimating the following panel specification at the plant-year level:

$$y_{ijz(s)t} = \alpha_i + \alpha_{jt} + \alpha_{st} + \sum_{\substack{b \in B \\ b \neq [15-18C)}} \beta_b D^b_{z(s)t} + \lambda X_{z(s)t} + \varepsilon_{ijz(s)t}, \tag{1}$$

where i denotes manufacturing plants, j indexes industries, $z(s)$ denotes the ZIP Code z in state s where the plant is located, and t denotes years. Our plant-year panel spans the time period from 1977 to 2018. The main independent variables, D^b, capture the number of days in a given ZIP Code and year whose maximum daily temperature is within a certain bin b. Our panel specification follows the approach of Deschênes and Greenstone (2011), which has been employed in estimating temperature impacts as it allows arbitrary non-linear relationships between temperature and outcome variables.[11] We divide the temperature distribution into 11 bins of 3°C each, ranging from strictly below 3°C to equal to or above 30°C. In all specifications, we exclude the temperature bin [15°C-18°C), which contains the median daily maximum temperature. The estimated β_b coefficients should be interpreted as the effect of an additional day with maximum temperature in a certain bin relative to an additional day with maximum temperature of 15°C-18°C. To account for geographical correlation in the error term, we cluster standard errors at the state-level in all specifications.[12] In addition, when examining outcome variables obtained from ASM/CMF (i.e., energy costs, productivity, and employment),

[10] See, for example, Auffhammer (2018), Burke and Emerick (2016), and Blanc and Schlenker (2017) for a comprehensive discussion of each method, as well as their advantages and drawbacks.

[11] See Zhang et al. (2018) and Heutel et al. (2021) for applications of the same methodology.

[12] Clustering at the state level is more conservative relative to clustering at finer geographic units, such as at the county or at the CZ level, since it allows standard errors to correlate within larger geographic areas. All our results are robust to, and more precisely estimated, when clustering standard errors at the county level or CZ level.

we estimate regressions using ASM sample weights.

Because plants have a fixed location over time, the inclusion of plant fixed effects (α_i) implies that the impact of temperature on outcomes is identified by deviations from plant-location-specific means. As such, we think of these yearly temperature shocks as random "weather" draws from the "climate" distribution in a given geographical area, and therefore as plausibly exogenous to the outcomes of interest (Dell et al., 2014). We layer additional fixed effects step-by-step to absorb potential time-varying industry and geographic dynamics that might confound our key estimates. We first include 3-digit NAICS industry fixed effects interacted with year fixed effects to absorb any aggregate trends at the industry-level experienced by U.S. manufacturing plants. We then add geographical identifier fixed effects (first Census Division, then State) interacted with year fixed effects to capture common trends in different areas of the US, which helps to ensure that the response of manufacturing to temperature shocks is identified by idiosyncratic local shocks.

Note that temperature shocks can affect local manufacturing activity in two ways. First, they can affect the input costs and production processes of plants, for example by increasing energy consumption, increasing maintenance costs of machinery and equipment or affecting the worker productivity. We think of this set of forces as manufacturing *supply* shocks. Additionally, temperature shocks can affect local consumer demand, for example via their impact on the profitability of local agriculture (Burke and Emerick, 2016). In the context of U.S. manufacturing, each ZIP code or CZ can be viewed as a small open economy and manufacturing as a tradable sector whose demand is geographically sparse across the U.S. and the rest of the world, and thus relatively independent from local demand shocks. Under this assumption, supply forces are likely to be the major driver of the impact of temperature on manufacturing outcomes. We test this assumption in the data by studying how temperature shocks affect energy costs and labor productivity, which are both observable in our data. We also present robustness tests on the role of local demand by restricting the sample to highly tradable sectors.

Temperature shocks might be associated with precipitation or extreme weather events, and thus affect manufacturing outcomes via this association. Figure A.3 reports the effect of an additional day with maximum temperature within each respective bin on average precipitation (Panel A) and the incidence of extreme weather events recorded in SHELDUS (Panels B to F). Additional hot days are associated with lower average precipitation, as well as lower probability of floods. Additional hot days are also mechanically associated with a higher probability of droughts and heatwaves, which are themselves defined based on the prolonged occurrence of high temperature days. The effect of temperatures on tornadoes and hurricanes are small and mostly insignificant. Given these findings, we augment equation (1) with a set of time-varying controls $X_{z(s),t}$ which include average precipitation and the occurrence of extreme weather events that are not mechanically associated with temperature, mainly hurricanes and tornadoes.

III.B Long differences approach to study the effects of climate change

To study the long-run response of manufacturing activity to changes in maximum temperatures, we aggregate data at the CZ level and estimate the following long difference specification:

$$\begin{aligned}\Delta y_{c(d),2010s-1980s} &= \alpha_d + \beta_1 \Delta CDD_{c(d),2010s-1980s} + \beta_2 \Delta HDD_{c(d),2010s-1980s} \\ &+ \lambda X_{c(d)} + u_{c(d)} \end{aligned} \tag{2}$$

To estimate equation (2), we construct decadal averages of yearly data for both the manufacturing outcome variables and the temperature variables in 1980-1989 and 2010-2019 in each CZ c in division d.[13] We calculate the long run differences by subtracting the decadal average of 1980-1989 from the decadal average of 2010-2019.

Our choice of start- and end-point is motivated by three observations. First, as outlined in Section II.B, the significant emergence of increases in temperature relative to historical averages occurred after 1981. Second, previous studies examining economic adaptation to long-run changes in temperature also focus on the post-1980 period, noting that warming trends in the U.S. after the 1980s have been larger than those observed in earlier periods (Burke and Emerick, 2016). Third, as explained in Section II.A, the U.S. Census LBD data provide consistent coverage of manufacturing activity for the 1980 to 2019 period, which is long enough to capture significant changes in the average climate of each location.

In equation (2), we use two parsimonious measures of temperature: cooling degree days (CDD) and heating degree days (HDD). These are standard measures meant to capture the energy required to keep temperature at a baseline level, and capture the non-linear impact of extreme temperature variation. Daily CDD is defined as the difference in degrees between the maximum daily temperature in a location and 18°C, which is the baseline temperature at which no heating or cooling is necessary, conditional on the maximum daily temperature being above 18°C.[14] For each CZ, we compute CDD as the sum of all $CDDs$ over a year. $HDDs$ are defined in the same way for days with a

[13] The U.S. Census Bureau divides U.S. states into 9 divisions: New England and Middle Atlantic in the Northeast region, East North Central and West North Central in the Midwest region, South Atlantic, East South Central and West South Central in the South region, and Mountain and Pacific in the West region.

[14] This implies that a day with maximum temperature of 20°C will correspond to 2 CDD and a day with maximum temperature of 12°C to 0 CDD. See, for instance, Heutel et al. (2021) or Zivin and Kahn (2016) for applications of $CDDs$ constructed relative to a baseline temperature of 65°F and Burke and Emerick (2016) for a CDD-type measure adjusted to the importance of temperature deviations during growing seasons in agriculture. See also the discussion by the National Oceanic and Atmospheric Service, `https://www.weather.gov/key/climate_heat_cool`.

maximum daily temperature below 18°C.

Equation (2) includes census-division fixed effects, which implies that the relevant variation identifying the coefficients β_1 and β_2 originate from within-division differences in climate trends across CZs. The inclusion of census-division fixed effects removes any role of unobservable regional trends. A potential concern is whether their inclusion also removes most of the relevant variation in long-term changes in climate. We investigate this concern in Figures 2 and 3.

Figure 2 reports the distribution of long-run changes in decadal averages of HDD and CDD. Panel (a) reports the distribution of these two variables in the raw data. As shown, between the 1980s and the 2010s, most U.S. CZs experience an increase in average yearly $CDDs$, or degree days above 18°C, while the changes in $HDDs$ are mostly negative. This is consistent with a significant warming trend in the U.S. during the last four decades. Panel (b) reports the distribution of long run changes in decadal averages of HDD and CDD that deviate from Census Division averages. As shown, even net of Census Division trends, there is significant variation in degree days across CZs. For example, a standard deviation in the raw distribution of long-run changes in CDD corresponds to about 90 degree days (see Table 1), while after removing division fixed effects, a standard deviation in the same variable corresponds to 71.7 degree days. We rely on this variation in our estimates of long-run effects of changes in average climate on manufacturing activity. Figure 3 reports the geographical distribution of these long-run changes in degree days that deviate from division-specific averages.

The key identifying assumption in equation (2) is that differential changes in degree days observed over the last four decades in each CZ are uncorrelated with other local trends that might also affect the outcomes of interest. Division fixed effects reduce the role of unobservables by removing aggregate trends across macro areas of the country. Still, a potential concern is that long-run changes in temperature might be correlated with unobservable CZ-level trends. In support of empirical approaches similar to the one in equation (2), previous papers in environmental economics have argued that "recent evidence from the physical sciences suggests that the large differential warming trends observed over the United States over the past few decades are likely due to natural climate variability" rather than trends in local emissions or changes in local land use (Burke and Emerick (2016), p.120). In support of this assumption, in Panel A of Table 2, we report the correlation between long-run changes in average temperatures and CZ-level initial characteristics, including population, per capita income, and share of college graduates among the adult population. We find no significant correlations with population, income per capita, or percentage of college graduates among the adult population. We also check the correlation of long-run increases in temperature with exposure to shocks that might be particularly important for U.S. manufacturing during our study period, such as import competition from China (Autor et al., 2013). Here we find a negative and significant correlation, which indicates that areas that have experienced faster warming within each Census Division were *less* affected by import competition from China in the early 2000s. Although this correlation is likely to – if anything – "attenuate" the negative impact of warming on manufacturing, we include the exposure to the China shock as a control in all our specifications.

We also test the correlation of long-run changes in temperature with long-run changes in frequency of reported natural disasters, such as floods, droughts, heatwaves hurricanes, and tornadoes, as well as long-run changes in average precipitation. Overall, in 2, we find non-significant correlations between changes in temperatures and changes in the frequency of natural disasters. As expected, we find that higher temperatures are negative correlated with long-run changes in average precipitation. In equation (2), we include the initial CZ characteristics reported in Panel A of Table 2, and also control for long-run changes in the natural hazards that are not mechanically a function of temperature (hurricanes and tornadoes) and average precipitation. We show that the magnitude of the point estimates is stable after the inclusion of these controls.

IV Results

We now discuss the results of our estimation of the short- and long-run effects of temperature on manufacturing plants.

IV.A Short-run response to temperature shocks

In this section, we discuss the short-run effects of temperature shocks on manufacturing outcomes. We start by focusing on two outcomes plausibly affected by an increase in hot days relative to the climate normally experienced in a given location: energy costs and productivity of manufacturing plants. Next, we examine the impact of temperature shocks on both the intensive margin (total value of shipment) and the extensive margin (exit) of manufacturing activity.

IV.A.1 Energy Costs

Manufacturing plants use electricity for production processes (e.g., to operate machinery), as well as for non-production processes (e.g., for temperature control of working environments). According to data from the Manufacturing Energy Consumption Survey reported in Figure A.4, around 80% of electricity consumption by U.S. manufacturers is used in production processes and 20% is used in non-production. Figure A.4 also shows that the majority of the electricity used in production processes is for machinery and equipment operations, as well as for refrigeration of inputs or outputs. Non-production electricity is used in similar shares for temperature control and lighting.

Higher than normal temperatures can increase energy costs for both production and non-production processes. In production, high temperatures generate higher resistance of components in electric motors, leading to lower performance and higher electricity consumption. They also increase the electricity needed for cooling and refrigeration of inputs and outputs. In non-production processes, higher temperatures increase electricity consumption for temperature control of work environments via air conditioning. Finally, higher temperatures can negatively affect the efficiency of energy production systems and transmission: an increase in the number of hot days implies that power plants need to be cooled down more often or cannot operate due to lower water availability. Energy transmission is also less efficient on hot days because electrons move slower at high temperatures inside transmission lines (Bartos et al., 2016).

We start by estimating equation (1) using plant-level total energy costs as the outcome variable. The results are reported in Table 3 columns (1)-(2) and visualized in Figure 4 (a). We define energy costs as the monetary value of expenses in electricity and fuel, normalized by the value of shipments at the plant level. As Table 1 shows, energy costs represent on average about 2.2% of total value of production. With an average profit margin among US manfucaturing firms of 10%, energy costs may represent on average about 22% of profits.[15] The point estimates should be interpreted as the effect of additional days in a given temperature bin relative to the omitted benchmark bins experienced by a given plant-location.

The results show that plants experiencing additional days with a maximum temperature above 18°C experience statistically significant increases in energy costs.[16] The effect is monotonically increasing in temperature bins. The magnitude of the coefficient on the highest temperature bin implies that a one standard deviation increase in the number of very hot days (days with maximum temperature equal or above 30°C) – which is 44.5 days – generates a 4.6% larger increase in energy costs.

In columns (3)-(4) of Table 3 we estimate equation (1) using as outcome variable electricity costs normalized by total value of production. The results are also visualized in Figure 4 (b). As Table 1 shows, electricity costs represent 61% of energy costs. The effects of temperature on electricity costs are similar in sign and magnitude to those on overall energy costs, and imply that a standard deviation larger increase in the number of very hot days generates a 4.2% larger increase in electricity costs.

We find no significant effects of additional cold days on energy costs. The asymmetry between the effects of additional hot days versus cold days on energy costs is prima facie surprising. One element that contributes to explain this finding is that – despite being less seasonal than residential or commercial energy consumption – industrial energy

[15] According to the 2024 Q3 US Census Quarterly Financial Report, between 2003 Q1 to 2024 Q3, the average profit per dollar of sales for the manufacturing sector is 10.1% before tax and 8.4% after tax.

[16] This is consistent with previous findings documented with smaller samples in the energy literature (Engle et al., 1986).

consumption displays large differences between summer and winter months. Data from the U.S. Energy Information Administration (EIA) reported in Figure A.5 (a) shows that during the summer months, average consumption in kilowatthours has been 9.6% higher than during the winter months in the years since 2002. Summer is also a period of higher energy prices faced by the industrial sector in the U.S. The EIA data reported in Figure A.5 (b) show that average electricity prices in cents per kilowatt hour for the industrial sector have been, on average, 10.5% higher during the summer months relative to the winter months between 2002 and 2023.[17] Taken together, these facts indicate that additional hot days during the summer generate higher marginal increases in energy costs for U.S. industrial plants than additional cold days in the winter period.

Next, we investigate the effect of temperature shocks on the energy costs of plants of different size. We define plant size based on the number of employees in the 1980s, and divide the plant size distribution into quintiles. To estimate the differential effect of temperature on the energy costs of small vs large plants, we include in equation (1) an interaction of the number of days in each temperature bin with a dummy capturing small plants (plants in the bottom 4 quintiles of the firm size distribution) as follows:

$$\begin{aligned} y_{ijz(s)t} &= \alpha_i + \alpha_{jt} + \alpha_{st} + \sum_{\substack{b\in B \\ b\neq[15-18C)}} \beta_b D^b_{z(s)t} + \sum_{\substack{b\in B \\ b\neq[15-18C)}} \gamma_b D^b_{z(s)t} \times 1(Small) \\ &+ \lambda X_{z(s)t} + \varepsilon_{ijz(s)t} \end{aligned} \tag{3}$$

The results of this specification are reported in Figure 5. The Figure reports both the estimated β_bs (Panel (a)), which capture the effect of temperature on large plants, and the estimated γ_bs (Panel (b)), which capture the differential effect of temperature on small plants relative to large plants. The estimates show that the effects of temperature shocks on energy costs are concentrated among small plants. Panel (a) shows that large manufacturing plants seem to be largely immune to the effects of temperature shocks on energy costs. On the other hand, small plants show positive effects of temperature shocks on energy costs that are statistically different than those of large plants. The magnitude of the coefficient on the number of days with maximum temperature in the hottest bin implies that a one standard deviation increase in the number of days equal or above 30 °C generates a 8% larger increase in energy costs for small firms (relative to no effect on large firms).

There are several potential explanations for this result. For example, large plants might be more likely to have implemented energy-saving technologies or operate with capital (e.g., machinery, equipment, buildings) that is more energy efficient and thus less

[17] Calculations done by the authors based on the Electric Power Monthly dataset available at `https://www.eia.gov/electricity/data.php`. We consider June to August as summer months, January to March as winter months.

sensitive to temperature shocks. For example, larger plants might be better insulated or have newer machinery and equipment used in production that are more energy efficient and less prone to overheating, thus requiring less cooling of production spaces. Consistent with this hypothesis, Ma et al. (2022) show that young firms, which are also smaller in size, tend to operate with older capital. In addition, conditional on the type of industry, smaller plants are likely to operate in smaller buildings with a higher surface-area-to-volume ratio (AVr). A higher AVr is associated with higher exposure to heat transfer and, thus, to outside temperatures. For example, Depecker et al. (2001) show the importance of the relationship between building shape and energetic consumption, documenting how a higher surface area-to-volume ratio is positively correlated with energy consumption .

IV.A.2 Productivity

Previous papers have documented a negative relationship between temperature and labor productivity (e.g., Graff Zivin and Neidell 2014, Heal and Park 2013, Hsiang 2010, and Somanathan et al. 2021). Rising temperatures can affect manufacturing productivity via their effect on both the performance of workers and the productivity of machinery and equipment. The effect of temperature on workers' productivity can arise due to fatigue and lower ability to focus, as well as absenteeism. Stricter safety standards have increased the amount of protective gear necessary in manufacturing workplaces over time, amplifying the exhaustion of performing the same task at a higher temperature. Another amplifying effect might arise from the faster physical pace or longer shifts set to meet production goals and remain competitive. On the other hand, direct evidence on the effects of temperature on the performance of machinery and equipment is sparse, although Zhang et al. (2018) show suggestive evidence that higher temperatures lower capital productivity for Chinese manufacturers.

We examine total factor productivity (TFP) in logs at the plant level. TFP is computed as the plant-level Solow residual. The results of estimating equation (1) when the outcome variables are log TFP are reported in Table 4 columns (1)-(2) and plotted in Figure 6. We also examine labor productivity, defined as valued added divided by the total number of employee-hours worked. The results for labor productivity are presented in columns (3)-(4). As before, point estimates should be interpreted as the effect of additional days in a given temperature bin relative to the average climate experienced at a given plant-location.

We find that temperature has a negative and monotonic effect on both measures of productivity, with additional days in hotter bins leading to lower productivity. The positive effects on additional cold days are small and mostly not statistically significant, while plants experiencing additional hot days experience significant declines in productivity. The magnitude of the coefficients implies that a one-standard-deviation increase in the number of "hot days" in the temperature bin with maximum temperature equal or above

30°C would generate a 1.5% decline in TFP and a 1% decline in labor productivity.[18]

Next, we investigate the heterogeneous effects of temperature shocks on productivity measured by TFP across plants of different size using the estimating equation (3). The results are reported in Figure 7. The effects of temperature shocks on the productivity of large plants are small and non statistically significant. On the other hand, higher than usual temperatures are associated with large and significant declines in the productivity of small plants. As shown by the point estimates on the interaction term, the effects on small plants' productivity are statistically different than those on large plants.

Potential explanations for these heterogeneous effects of temperature shocks on plant productivity include heterogeneity in the type of labor and capital used by plants of different size. Larger plants use physical capital whose performance is less affected by abnormal temperatures, have more advanced temperature control systems (Zivin and Kahn, 2016), or better insulated work environments. Differences in the type of labor force employed in large versus small plants might also play a role. For example, large plants may have employees who are more productive, more motivated, and whose performance may be less affected by temperature shocks.

We next discuss the relationship between the effects of temperature on energy costs and productivity. Higher energy expenditure increases plant costs but might also help to partly absorb the impact of temperatures on worker productivity thanks to temperature control systems. This relationship between energy expenditure and productivity is hard to test as we do not observe how manufacturing plants use energy.[19] However, the evidence presented in Figures 5 and 7 show that – within narrowly defined sectors – we observe both an increase in energy costs and a decline in productivity within small plants. This suggests that at least some small plants have less energy-efficient equipment and temperature control systems, so that higher temperatures both increase their costs and decrease their productivity.

[18]Because energy is an input in production, the increase in energy costs documented above could mechanically generate a decline in value added, and thus in TFP or labor productivity measured as value added per worker. We checked this potential explanation of the productivity results by estimating equation (1) using an alternative measure of productivity in which value added is constructed without including energy among inputs. The results of this robustness test are reported in Table A.2 columns (3)-(4). As shown, we find similar results using this alternative measure, which indicates that the effect of temperature shocks on productivity is not mechanically driven by the effect of temperature shocks on energy costs.

[19]Data from the ASM/CMF shows that the majority of energy expenditures are in electricity rather than fuel. In addition, data from the Manufacturing Energy Consumption Survey shows that, on average, about 80% of electricity is used by manufacturing plants for their production process (e.g., operating machinery and equipment, including heating, cooling and refrigeration of inputs and outputs), about 9% is used for temperature control of work environment, and another 7% for lighting.

IV.A.3 Intensive and extensive margin

Finally, we study whether manufacturing plants respond to temperature shocks via the intensive margin (e.g., by increasing or decreasing their size) or via the extensive margin (e.g., by deciding to exit certain locations). We start by studying the effect of temperature shocks on plant size, as measured by its total value of shipment. The results are reported in column (1) of Table A.3. We find no contemporaneous response of firm size to additional hot days relative to what is normally experienced by a given plant, and a positive but noisy response to additional cold days.

Next, we focus on the extensive margin as measured by plant exit from a given zip code. To this end, we use data from the LBD described in Section II.A, which tracks all manufacturing establishments, along with their location over time. When estimating equation (1), we define exit in year t as a dummy equal to 1 if plant i has positive employment in the LBD in year t but no recorded employment in year $t+1$. This is because plants that operate for a fraction of a year are still recorded in the LBD for that year, so our definition ensures that we are capturing the contemporaneous relationship between temperature shocks and exit decisions. The results are reported in column (2) of Table A.3. We find that the effect of temperature shocks on exit is mostly small in magnitude and non statistically significant. The probability of exit monotonically increases with temperature bins above 18°C but even estimates on the highest temperature realizations are not statistically significant.

IV.A.4 Robustness Tests

There are two potential concerns with the interpretation of our results. First, temperature shocks can affect local demand from consumers. Although the manufacturing sector mostly produces tradable goods sold in the rest of the U.S. or internationally, it is possible that the demand for some manufacturing goods is still local. To test for this concern, in Table A.4, we replicate our analysis restricting the sample to manufacturing sectors with high (above median) levels of tradability according to the geographical concentration index proposed in Mian and Sufi (2014). Results are quantitatively similar when implementing this restriction.

Another potential concern is that extreme temperature realizations that are detrimental for crop yields can negatively affect manufacturing production via input-output linkages with local agriculture. To deal with this concern, in Table A.5, we replicate our analysis excluding manufacturing sectors for which agricultural output is a main input in production. In particular, we exclude manufacturing sectors for which expenditures in inputs from agriculture is 5% or more of total value of production according to the earliest (1980) available Input-Output table from the Bureau of Economic Analysis (i.e. manufacturing of food, beverage and tobacco products). Results are robust to this sample restriction.

Finally, in Table A.6 we show that the main results on short-run effects of temperature shocks are robust to alternative definitions of temperature. In Panel A, we use bins constructed using average daily temperatures instead of maximum daily temperatures. In Panel B, we use a continuous measure of temperature deviations, Cooling Degree Days (CDD) and Heating Degree Days (HDD) as defined in section III.B. As shown, the results are robust to these alternative definitions.

IV.B Long-run response to changes in temperature

The short-run responses to temperature shocks documented in Section IV.A indicate that small plants incur significant additional energy costs and lower productivity in hotter than usual years. However, these effects do not trigger significant contemporaneous adjustments on the intensive or extensive margin. It is plausible that key industrial decisions such as reducing the size of an existing plant or exiting a given market are not driven by yearly weather shocks, especially if such shocks are interpreted as idiosyncratic and therefore likely to revert. On the other hand, the cumulative effect of several years of hotter than usual weather might push managers to respond on these margins. This is because a series of deviations from past temperatures might indicate a shift in the climate distribution from which weather events are drawn in a given geographical area.

To investigate the response to long-run changes in average temperatures in a given CZ, we estimate equation (2) described in section III.B. This equation relates long-run changes in manufacturing activity to long-run changes in average temperatures between the 1980s and the 2010s. As discussed in section II.B, the U.S. experienced a large increase in average temperatures between the 1980s and 2010s, with substantial variation even across CZ within the same areas of the country.

We start by studying the effect of long-run changes in temperature on number of plants, total employment, and average plant size in a given CZ. The results are reported in Table 5. The point estimate in column (1) indicate that CZs that have become warmer over the last four decades experience a relative decline in the number of plants. The magnitude of estimated coefficient implies that a standard deviation higher increase in temperature – about 90 degree days above 18°C per year – corresponds to a 4.2% percent larger decline in the number of manufacturing plants. We find no significant effects of long-run temperature changes on total employment, leading to a positive – thought not statistically significant – effect on the average plant size. Overall, these results indicate that CZs with faster warming temperatures experienced higher exit and no significant changes in total employment, which is consistent with a reallocation of workers towards larger plants.

We then focus on the impact of long-run changes in temperature on local concentration of manufacturing activity. We bring the analysis to the CZ-sector level, where sectors are constructed based on the NAICS 3-digit classification. We estimate a version of equation (2) including both Census division and sector fixed effects. In terms of outcomes, we focus on the share of employment concentrated in the top-4 largest plants and the Herfindahl-Hirschman Index (HHI) in a given CZ-industry. We compute the HHI as the sum of squared values of the employment shares of each plant in a given CZ-industry. The HHI thus captures the amount of concentration in the employment share across plants, with higher values indicating higher concentration.

The results are reported in panel A of Table 6. The point estimates indicate positive and significant effects of long run changes in average temperatures on industrial concentration. In particular, we find that manufacturing sectors in CZs that in the 2010s decade had a standard deviation higher increase in temperature relative to the 1980s decade experienced a 0.5 percentage points larger increase in the share of employment concentrated in the top 4 largest plants, and a 3 percent larger increase in the HHI. Overall, the results indicate that faster warming in the last four decades has led to higher concentration of industrial activity among larger plants within manufacturing sectors.

IV.C Mechanisms behind long-run response

The finding that faster warming led to higher concentration of manufacturing activity among large plants suggests that such plants are better equipped for long-run adaptation to climate change. In this section, we discuss and empirically test potential mechanisms that can rationalize this result. To this end, we estimate a version of equation (2) at the CZ-industry level in which the measure of long-run changes in temperature $\Delta CDD_{c(d)}$ is interacted with variables capturing exposure to different mechanisms. We consider four potential mechanisms: energy prices, managerial skills, access to finance, and ability to hedge across locations.

IV.C.1 Energy prices

The latest U.S. Manufacturing Energy Consumption Survey, which was run in 2018 on a nationally representative sample of manufacturing establishments, shows that establishments with fewer than 50 employees face electricity prices (in USD per m BTU) that are 33% higher than those faced by manufacturing establishments with 50 employees and above.[20] The reason is that large manufacturing plants can negotiate better prices from electricity suppliers because they use more electricity, and can receive it at higher voltages, making electricity transmission less expensive. In addition, their demand is less seasonal and less volatile during the day, which allows them to negotiate discounts in exchange for lowering their energy usage during consumption peaks by retail customers that put the electric grid under stress.

[20]See Table 7.5, MECS publication, released in September 2021.

For a given increase in energy demand, higher prices per unit of energy translate into larger cost shocks for small than for large plants. Over the long run, more hot days can lead to a higher frequency of such cost shocks for small plants. This is a potential mechanism behind the relative decline in both the number and the employment share of small plants in regions that experienced faster warming during the last four decades.

To test this mechanism, we interact long-run changes in temperature at CZ level with a dummy capturing above-median electricity prices (in dollars per unit of energy) at the NAICS-3 industry and Census region level. As shown in Figure A.6, average electricity prices per unit of energy are highly correlated with the price gap between small and large plants at the division-year level. Notice that, although MECS reports information on electricity prices for plants with employment above versus below 50 employees, this information is only available aggregated at the Census division level (9 divisions), providing limited cross-sectional variation. Thus, when testing this mechanism, we exploit variation in baseline average electricity prices, which is available at the industry-Census region level.[21]

The results are reported in Panel B of Table 6. We find that long-run changes in temperature have no effect on concentration in industry-regions facing below-median cost per unit of energy. The effect is positive and statistically significant for industry-regions facing higher energy costs. In particular, for a given increase in long-run temperatures, industry-regions with above-median energy costs experience a 1.2 percentage points larger increase in the share of employment in the top 4 largest plants and a 4.3 percent larger increase in HHI relative to industry-regions facing below-median energy prices. There results are consistent with energy prices being an important transmission mechanism, linking warming temperatures to industry concentration over the long run.

IV.C.2 Managerial skills

Large plants might also have better trained managers who understand the change in exposure to climate risk and invest in adaptation. This hypothesis relies on two findings documented in previous studies. First, there is evidence that large firms tend to be better managed. For example, Bloom et al. (2019) document large dispersion in management practices across U.S. manufacturing plants, and show that the diffusion of "structured" management practices is strongly correlated with both plant and firm size as captured by number of employees (Figure A2 in Bloom et al. 2019).

Second, previous work also establishes that better managed firms are less energy intensive and more productive (Bloom et al. 2010, Martin et al. 2012), and that more attentive managers are able to offset some of the adverse effects of warmer temperatures on produc-

[21] Ideally, we would like to use a baseline measure of electricity prices faced by plants in a given industry and region at the beginning of our sample. However, the MECS data starts in 1998, so we sort industry-regions based on the 1998 distribution of prices per unit of energy in that year.

tivity by means of task reallocation (Adhvaryu et al. 2022). Within our setting, examples of investments in adaptation include the adoption of technologies that reduce the effect of temperature on labor productivity, such as automated warehouse management systems, the updating of buildings and machinery so that they can better withstand higher temperatures or natural disasters, and the adoption of general energy-saving technologies such as computer systems to control major energy-using equipment.

In order to test this mechanism, we exploit data on participation in electricity management practices at the industry-level from the Manufacturing Energy Consumption Survey (MECS) of 1998. We sort industries by their baseline participation rate in such practices and estimate the heterogeneous effects of long-run changes in temperatures across industries with different participation rates. The results are reported in Panel C of Table 6. Consistent with the channel entertained in this section, we find that higher participation rates in electricity management lead to a lower impact of long-run changes in temperatures on industry concentration.

IV.C.3 Access to finance

Another potential mechanism linking firm size to adaptation to climate change is that large plants might have better access to external finance. This would allow them to use available credit lines to cope with weather shocks, reducing the need to downscale employment or close plants. For example, using data from Brazil, Albert et al. (2021) document how access to finance helped drought-affected municipalities to insure themselves against the negative impact of weather shocks via capital inflows from regions connected via the bank branch network. Easier access to external finance also facilitates investments in long-term projects necessary to make their production process less sensitive to climate change. In the context of agriculture, Rajan and Ramcharan (2023) document that access to bank finance facilitated the long-run adjustment to the 1949-1957 drought in the US. They show that counties with initially better access to external finance experienced lower out-migration, and their agricultural sector was better able to adapt via investments in irrigation, drought-tolerant crops, and mechanization.

To test this mechanism, we exploit variation in the density of bank branches per capita across CZs as a proxy for local financial development and ability to access bank financing for small and medium plants. Data on bank branch locations is from the FDIC, with the caveat that the first year for which data is available is 1994. In our test, we rely on variation across locations (CZs) as opposed to variation across industries or industry-locations used in the previous tests.

The results are reported in Panel D of Table 6. We find positive effects of long-run changes in temperatures on local industry concentration in areas with below-median local bank branch density. The coefficients on the interaction with above-median bank branch density are negative but not statistically significant. Overall, these results are noisy – and our proxy of access to external finance too general to be able to draw strong conclusions about the role of access to finance on adaptation in our setting.

IV.C.4 Hedging across locations

Large firms that operate across multiple plants in different locations might be naturally better hedged to absorb weather shocks, even when they occur at higher frequency due to climate change. For example, Castro-Vincenzi (2022) documents how car companies are able to partly absorb weather shocks, such as floods, by reallocating production from affected plants to non-affected plants. This hedging strategy requires to keep spare capacity in each location, which firms with multiple plants are more likely to be able to afford. Similarly, Acharya et al. (2023) show that U.S. firms operating in multiple locations reallocate employment from counties affected by heatwaves to unaffected counties, while single-plant firms are more likely to downsize in response to such shocks.

Data from the National Establishment Time Series (NETS) indicates that, in US manufacturing, large plants are more likely than small plants to be part of a multi-unit firm. In particular, 56% of plants with more than 20 employees and 67% of plants with more than 50 employees are part of a multi-unit firm. On the other hand, only 17.5% of plants with up to 20 employees and 21.4% of plants with up to 50 employees are part of a multi-unit firm.

To test the potential role of hedging across multiple plants, we investigate whether the effects of long-run changes in temperature on concentration differ depending on whether local small plants are single-unit firms or part of a multi-unit firm. The hedging mechanism described above would imply that small plants that are part of a multi-unit firm should be better able to cope with the negative effects of long-run increases in temperature, leading to a lower impact of higher temperatures on local industry concentration. We use data from the U.S. Census Bureau and sort CZ-industries by the share of small plants (plants in the first quintile of the size distribution) that are part of multi-unit firms in the 1980s (decadal average). The results are reported in Panel E of Table 6. We find the long-run effects of changes in temperature on concentration to be partly attenuated when a larger fraction of local small plants is part of multi-unit firms.

V Conclusions

In this paper, we use plant-level data from the U.S. Census of Manufacturers to study the short and long-run effects of temperature variation on manufacturing activity. Taken together, the results are consistent with large plants being better equipped to adapt to climate change. Our evidence indicates that differences in costs per unit of energy, managerial skill, and – to a more limited extent – hedging across locations play an important role. Our results highlight that recent increases in industry concentration might not solely be due to technological or political factors, but also to better adaptation to climate change.

The results also raise the question of whether higher concentration of employment within large plants is "good or bad" for the local economies more affected by a warming climate. We do not address the welfare implications of manufacturing concentration driven by climate change in this paper. However, some of our results speak to this debate. For example, the presence of large plants with the means to adapt to climate change could be an important factor in preserving employment locally and limiting out-migration. Indeed, our results show that faster warming leads to a reallocation of employment from small to large plants but no significant changes in the overall employment at the county level. On the other hand, the differential effect of temperature across plants of different size might have detrimental effects on outcomes associated with small scale firms – such as "radical" innovations, as previous literature suggested (Prusa and Schmitz Jr, 1991) – or even constitute a barrier to entrepreneurship in certain regions. All these are important avenues for future research.

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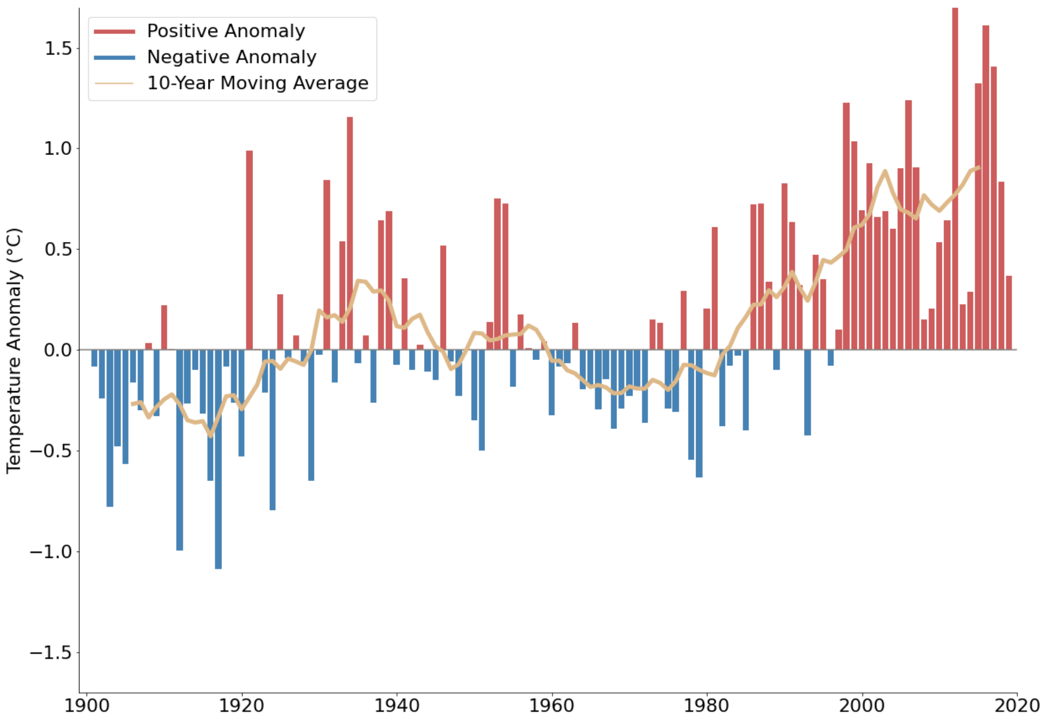
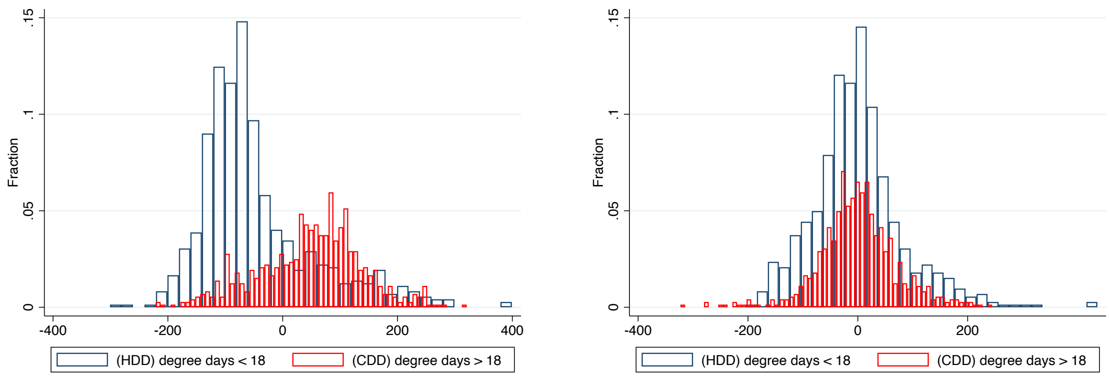
Figure 1: Temperature trend in the U.S.



Notes: The figure shows annual and decadal temperature dynamics over the 1901 to 2019 period on the basis of temperature data obtained from the National Oceanic and Atmospheric Administration (NOAA). The underlying data covers 48 contiguous states. Annual anomalies (the bars) are defined as the difference between the annual average temperature across the 48 states and the average annual temperature over the 1901 to 2000 period. The moving average of the anomaly (line) is based on 10 years of anomaly observations centered around years [-4;5].

Figure 2: Distribution of the long-run changes in degree days above and below 18°C

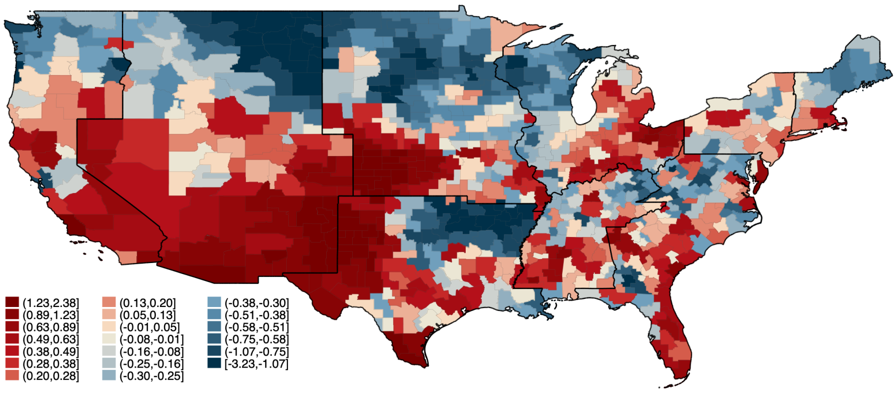
(a) Raw changes (b) Changes residualized on Census Division FE



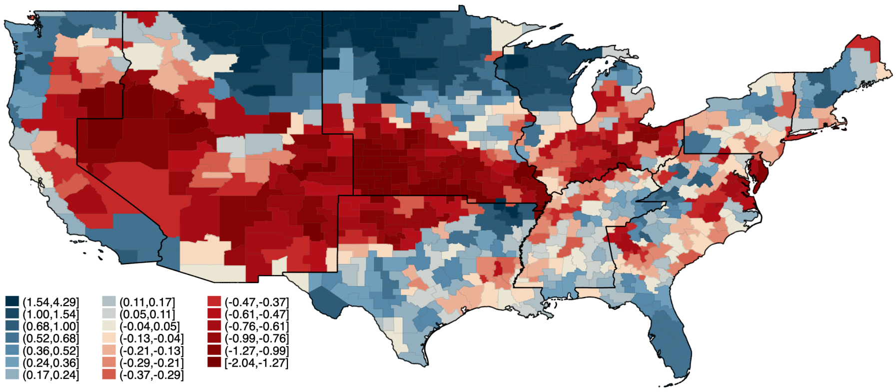
Notes: The figure shows the distribution of changes in heating degree days (HDD; blue) and cooling degree days (CDDs; red) from the 1980s to the 2010s at the commuting zone level. A daily CDD is the difference in degrees between the maximum daily temperature and 18°C conditional on the maximum daily temperature being above 18°C, and a daily HDD is the difference in degrees between 18°C and the maximum daily temperature conditional on the maximum daily temperature being below 18°C, see Heutel et al. (2021) or Zivin and Kahn (2016). For each commuting zone, average daily HDDs and CDDs are summed by year; yearly HDDs and CDDs are then averaged over the 2010s and 1980s, respectively, from which the long-run difference is calculated. Underlying data are from the PRISM Climate Group (we use the cleaned version of that data provided on Wolfram Schlenker's homepage). Panel A shows raw data, and Panel B shows the distribution after removing Census Division fixed effects.

Figure 3: Geographic distribution of long-run changes in degree days above and below 18°C

(a) Δ (degree days > 18°C or CDDs)



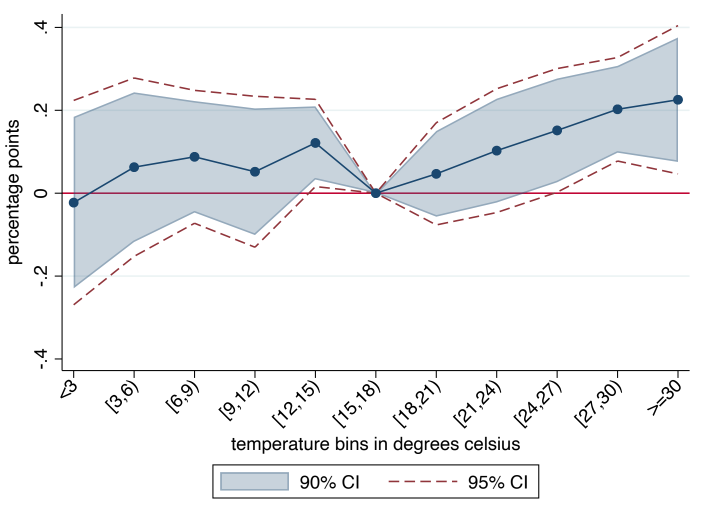
(b) Δ (degree days < 18°C or HDDs)



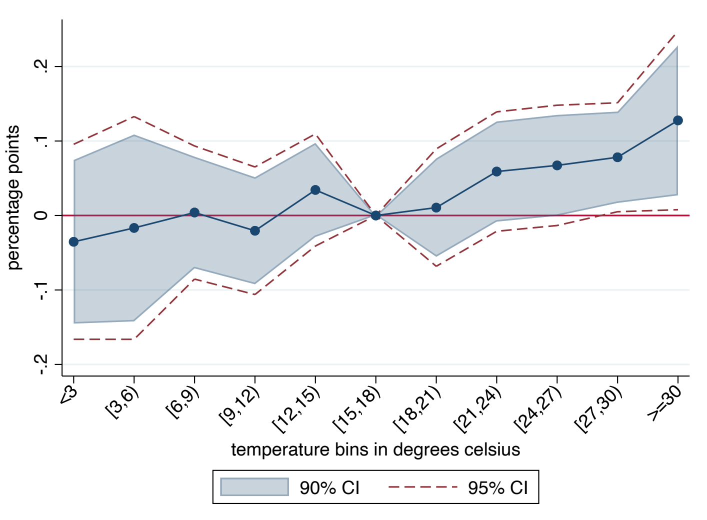
Notes: The figure shows changes in Cooling Degree Days (CDDs, Panel A) and Heating Degree Days (HDDs, Panel B) between the 1980s and the 2010s by commuting zone relative to average Census division changes. A daily Cooling Degree Day (CDD) is the difference in degrees between the maximum daily temperature and 18°C conditional on the maximum daily temperature being above 18°C, and a daily Heating Degree Day (HDD) is the difference in degrees between 18°C and the maximum daily temperature conditional on the maximum daily temperature being below 18°C, see Heutel et al. (2021) or Zivin and Kahn (2016). For each commuting zone, average daily HDDs and CDDs are summed by year, yearly HDDs and CDDs are then averaged over the 2010s and 1980s, respectively, from which the long-run difference is calculated. Underlying data is from the PRISM Climate Group (we use the cleaned version of that data provided on Wolfram Schlenker's homepage). Red indicates counties that have become warmer, i.e., that experienced an increase in CDDs (Panel A) or a decrease in HDDs (Panel B) relative to division-level changes.

Figure 4: Short-run effect of temperature on energy costs (as a percentage of the total value of shipments)

Panel A: Energy Costs/Total Value of Shipments



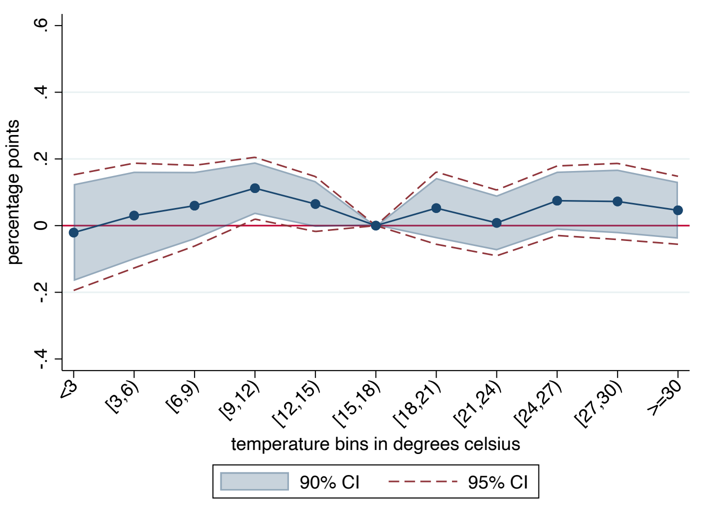
Panel B: Electricity Costs/Total Value of Shipments)



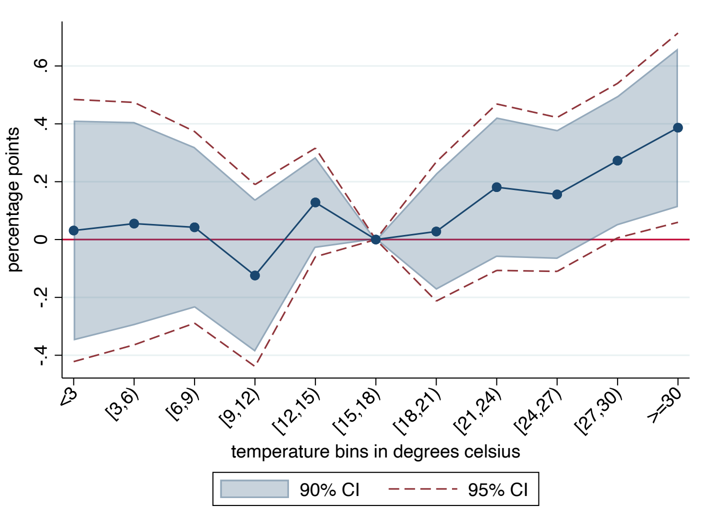
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments (Panel (a)) and electricity costs divided by total value of shipments (Panel (b)). The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days of maximum temperatures in each respective temperature bin (β_b in equation (1)) in a given year in a plant's ZIP Code. The number of days in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. Control variables include average zip code-year level precipitation, as well as number of hurricanes and number of tornadoes at the county-year level. Plant, industry-year, and state-year fixed effects are also included. Underlying regressions are estimated using ASM sample weights.

Figure 5: Heterogeneous effects on Energy Costs/Total Value of Shipments by Plant Size

Panel A: Large Plants



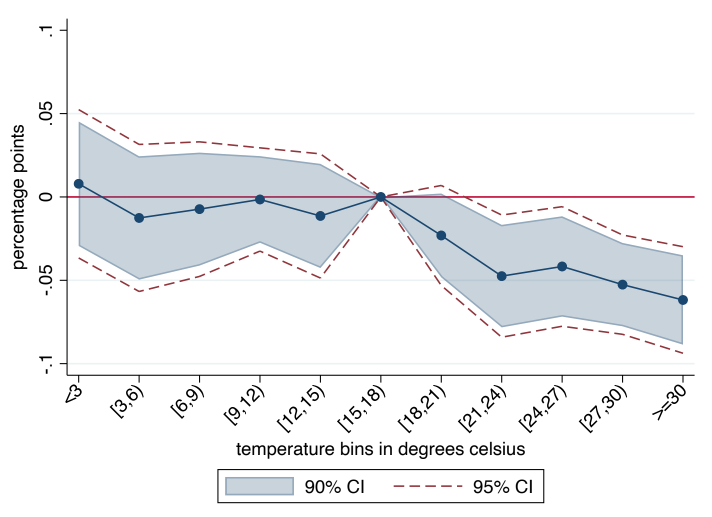
Panel B: Difference between Small and Large Plants



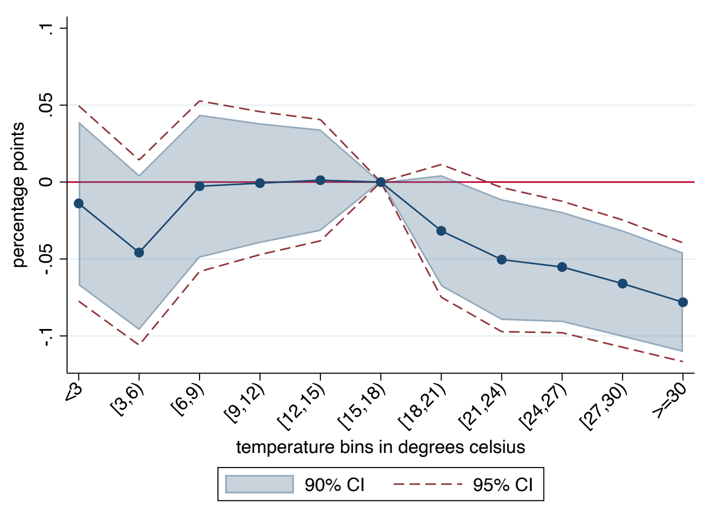
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments on large firms (Panel (a)) and small firms (Panel (b)). The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days of maximum temperatures in each respective temperature bin (β_b in equation (1)) in a given year in a plant's ZIP Code. The number of days in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. We define plant size based on the number of employees in the 1980s, and divide the plant size distribution into quintiles. Small plants are those in the smallest quintile; large plants are all other plants. Control variables include average zip code-year level precipitation, as well as number of hurricanes and number of tornadoes at the county-year level. Plant, industry-year, and state-year fixed effects are also included. Underlying regressions are estimated using ASM sample weights.

Figure 6: Short-run effect of temperature on productivity

Panel A: Log(TFP)



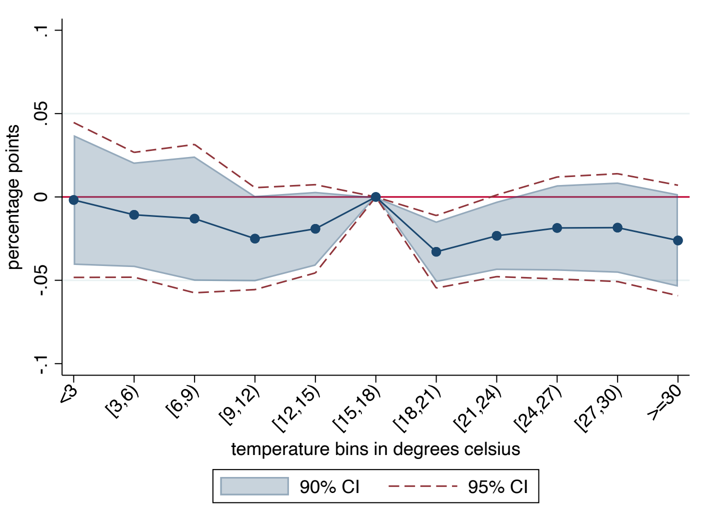
Panel B: Log(Value-Added / Total Hours Worked)



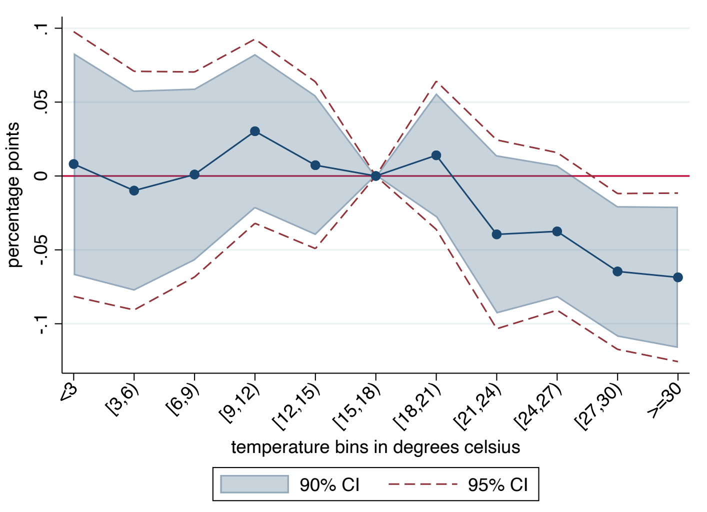
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP). The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days of maximum temperatures in each respective temperature bin (β_b in equation (1)) in a given year in a plant's zip code. The number of days in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. Control variables include average ZIP Code-year level precipitation, as well as number of hurricanes and number of tornadoes at the county-year level. Plant, industry-year, and state-year fixed effects are also included. Underlying regressions are estimated using ASM sample weights.

Figure 7: Heterogeneous short-run effects of temperature on Log(TFP)

Panel A: Large Plants



Panel B: Difference between Small and Large Plants



Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP) on large firms (Panel (a)) and small firms (Panel (b)). The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days of maximum temperatures in each respective temperature bin (β_b in equation (1)) in a given year in a plant's zip code. The number of days in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. We define plant size based on the number of employees in the 1980s, and divide the plant size distribution into quintiles. Small plants are those in the smallest quintile; large plants are all other plants. Control variables include average ZIP Code-year level precipitation, as well as number of hurricanes and number of tornadoes at the county-year level. Plant, industry-year, and state-year fixed effects are also included. Underlying regressions are estimated using ASM sample weights.

Table 1: Summary Statistics

Variables	N	Mean	Std. Dev.
Panel A: ASM & CMF Sample			
Energy Costs/Total Value of Shipments (%)	1922000	2.20	2.91
Electricity Costs/Total Value of Shipments (%)	1922000	1.34	1.58
Log(TFP)	1922000	1.85	0.56
Log(Value-Added / Total Hours Worked)	1922000	3.47	0.91
Log(Total Value of Shipments)	1922000	9.43	1.66
T < 3°C	1922000	35.40	33.53
3°C ≤ T < 6°C	1922000	17.92	12.55
6°C ≤ T < 9°C	1922000	20.16	12.28
9°C ≤ T < 12°C	1922000	22.54	11.83
12°C ≤ T < 15°C	1922000	26.17	10.87
15°C ≤ T < 18°C	1922000	29.78	10.28
18°C ≤ T < 21°C	1922000	33.21	11.66
21°C ≤ T < 24°C	1922000	37.01	12.83
24°C ≤ T < 27°C	1922000	42.84	13.01
27°C ≤ T < 30°C	1922000	44.59	15.11
T ≥ 30°C	1922000	55.61	44.48
Panel B: LBD Sample			
Exit	13590000	0.08	0.26
Panel C: LBD - Long-run diff. at the commuting zone level			
Δ Degree-Days > 18°C	700	48.63	90.06
Δ Degree-Days < 18°C	700	-46.83	98.34
Δ Log(# Estab.)	700	-0.02	0.30
Δ Log(Emp.)	700	-0.22	0.54
Δ Log(Avg. Size of Estab.)	700	-0.20	0.43
Panel D: LBD - Long-run diff. at the commuting zone-NAICS 3 level			
Δ Degree-Days > 18°C	11000	53.08	80.49
Δ Degree-Days < 18°C	11000	-56.81	83.18
Δ Fraction of Emp. in Top 4 Largest Estab.	11000	-0.00	0.11
Δ Log(HHI_Emp.)	11000	0.00	0.54

Notes: The table shows summary statistics for the ASM and CMF sample at the plant-year level (Panel A), the LBD sample at the plant-year level (Panel B), and long-run differences (average in the 2010s minus average in the 1980s) for the LBD sample at the commuting zone level (Panel C) and commuting zone-industry level (Panel D). Variable definitions are in Appendix Table A.1.

Table 2: Balance test for commuting zone initial characteristics

	Δ Degree-days > 18 / 100 (1)	R-squared (2)
Panel A: Commuting zone initial characteristics		
perc. of college grads	0.185	0.325
	(0.121)	
log(pop.)	-0.036	0.277
	(0.104)	
log(per cap. income)	0.088	0.199
	(0.118)	
ΔIPW_{uit}	-0.311***	0.191
	(0.071)	
Panel B: Long-run changes in the occurrences of natural hazards		
avg. precipitation	-0.153	0.298
	(0.154)	
flood	-0.095	0.076
	(0.102)	
drought	-0.026	0.217
	(0.113)	
heatwave	-0.009	0.135
	(0.118)	
hurricane	-0.146	0.221
	(0.099)	
tornado	-0.217*	0.119
	(0.124)	
Observations	722	

Notes: Outcome variables in the regressions for columns (1)-(3) of Panel A are commuting zone characteristics observed in 1980 Census. The outcome variable in the regression for column (4) of Panel A is the changes in exposure to China shock between 1991 and 2007, as is defined in Autor et al. (2013). The last two rows in Panel A report the mean and standard deviation of the corresponding outcome variable in each column. The outcome variables in the regression for Panel B is the difference between the occurrences of each natural disaster in the 1980s and the 2010s. The independent variables in both panels are the changes in the number of degree days above 18°C from the 1980s to the 2010s. The long-run changes in degree days below 18°C are also controlled in all specifications. The independent variables are divided by 100 to make the table easier to read. Standard errors are reported in parentheses and clustered at the state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Short-run effect of temperature on energy costs

	Energy Costs/TVS		Electricity Costs/TVS	
	(1)	(2)	(3)	(4)
T < 3°C	0.021	-0.0227	-0.0076	-0.0353
	(0.0674)	(0.1258)	(0.0434)	(0.0668)
3°C ≤ T < 6°C	0.0986	0.0628	-0.0095	-0.0167
	(0.0632)	(0.1098)	(0.0459)	(0.0763)
6°C ≤ T < 9°C	0.0535	0.0878	-0.0087	0.004
	(0.0667)	(0.0818)	(0.0422)	(0.0456)
9°C ≤ T < 12°C	0.0714	0.0518	0.0035	-0.0205
	(0.0705)	(0.0929)	(0.0351)	(0.0437)
12°C ≤ T < 15°C	0.0772	0.1213**	0.009	0.0343
	(0.0501)	(0.0537)	(0.0342)	(0.0384)
18°C ≤ T < 21°C	0.0629	0.0467	0.021	0.0106
	(0.0520)	(0.0629)	(0.0353)	(0.0402)
21°C ≤ T < 24°C	0.1277*	0.1027	0.0780*	0.059
	(0.0690)	(0.0762)	(0.0440)	(0.0409)
24°C ≤ T < 27°C	0.1454***	0.1515*	0.0653**	0.0673
	(0.0490)	(0.0761)	(0.0312)	(0.0412)
27°C ≤ T < 30°C	0.1578***	0.2025***	0.0665**	0.0782**
	(0.0520)	(0.0637)	(0.0317)	(0.0373)
T ≥ 30°C	0.1606**	0.2255**	0.0937**	0.1277**
	(0.0617)	(0.0913)	(0.0427)	(0.0612)
Observations	1922000	1922000	1922000	1922000
R-squared	0.790	0.791	0.764	0.766
Establishment FE	yes	yes	yes	yes
NAICS3-Year FE	yes	yes	yes	yes
Extreme weather controls	yes	yes	yes	yes
Census Division-year FE	yes		yes	
State-year FE		yes		yes

Notes: The table uses the panel data approach described in Equation (1) to estimate the short-run effects of temperature on energy costs divided by total value of shipments (Columns 1-2) and electricity costs divided by total value of shipments (Columns 3-4). The analysis is at the plant-year level and the sample period comprises 1977-2018. The shown coefficients of interest represent the number of days in each respective temperature bin (β_b in equation (1)) in a given year in a plant's zip code. The number of days with maximum daily temperature in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. All specifications control for average ZIP Code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at the 1% (***), 5% (**), and 10% (*) level.

Table 4: Short-run effect of temperature on productivity

	Log(TFP)		$\text{Log}(\frac{\text{Value-Added}}{\text{Total Hours Worked}})$	
	(1)	(2)	(3)	(4)
T < 3°C	-0.0003	0.0079	-0.0159	-0.0139
	(0.0149)	(0.0227)	(0.0219)	(0.0324)
3°C ≤ T < 6°C	-0.018	-0.0126	-0.0324*	-0.0458
	(0.0179)	(0.0225)	(0.0190)	(0.0307)
6°C ≤ T < 9°C	-0.0066	-0.0073	0.0092	-0.0027
	(0.0144)	(0.0206)	(0.0225)	(0.0283)
9°C ≤ T < 12°C	-0.0087	-0.0015	-0.0022	-0.0007
	(0.0127)	(0.0158)	(0.0187)	(0.0237)
12°C ≤ T < 15°C	-0.0114	-0.0114	0.0077	0.0012
	(0.0154)	(0.0190)	(0.0175)	(0.0201)
18°C ≤ T < 21°C	-0.0131	-0.0231	-0.0173	-0.0317
	(0.0121)	(0.0153)	(0.0191)	(0.0220)
21°C ≤ T < 24°C	-0.0292**	-0.0475**	-0.0314	-0.0504**
	(0.0130)	(0.0187)	(0.0195)	(0.0239)
24°C ≤ T < 27°C	-0.02	-0.0417**	-0.0324*	-0.0552**
	(0.0127)	(0.0183)	(0.0184)	(0.0218)
27°C ≤ T < 30°C	-0.0353***	-0.0526***	-0.0503***	-0.0660***
	(0.0111)	(0.0152)	(0.0174)	(0.0211)
T ≥ 30°C	-0.0346***	-0.0618***	-0.0487***	-0.0781***
	(0.0104)	(0.0163)	(0.0158)	(0.0197)
Observations	1922000	1922000	1922000	1922000
R-squared	0.777	0.778	0.779	0.78
Establishment FE	yes	yes	yes	yes
NAICS3-Year FE	yes	yes	yes	yes
Extreme weather controls	yes	yes	yes	yes
Census Division-year FE	yes		yes	
State-year FE		yes		yes

Notes: The table uses the panel data approach described in Equation (1) to estimate the short-run effects of temperature on total factor productivity (Columns 1-2) and value added divded by total hours worked (Columns 3-4). The analysis is at the plant-year level and the sample period comprises 1977-2018. The shown coefficients of interest represent the number of days in each respective temperature bin (β_b in equation (1)) in a given year in a plant's zip code. The number of days with maximum daily temperature in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 5: Long-run effects of temperature on number of plants, employment, and plant size

	Δ Log(# Estab.) (1)	Δ Log(Emp.) (2)	Δ Log(Avg. Size of Estab.) (3)
Δ Degree-Days > 18°C	-0.0465**	0.0093	0.0535
	(0.0209)	(0.0462)	(0.0421)
Δ Degree-Days < 18°C	-0.0306	0.0062	0.036
	(0.0305)	(0.0413)	(0.0302)
Observations	700	700	700
R-squared	0.233	0.223	0.173
Census Division FE	yes	yes	yes
Commuting zone controls	yes	yes	yes

Notes: The table reports results obtained by estimating the commuting-zone-level long-run specification described in equation (2). Δ Degree-Days > 18°C is divided by 100 for readability. In column (1), the left-hand side variable is the change in the natural logarithm of the average yearly number of establishments between the 2010s and the 1980s. In column (2), the left-hand side variable is the change in the natural logarithm of the average yearly number of employees reported by establishments between the 2010s and the 1980s. In column (3), the left-hand side variable is the change in the natural logarithm of the average number of employees per establishment between the 2010s and the 1980s. CZ-level controls include: change in average precipitation between the 2010s and the 1980s, percentage of population that attended at least one year of college in 1980, log-transformed population in 1980, log-transformed income per capita in 1980, change in exposure to the China shock between 1990 and 2007, and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 6: Heterogeneous long-run effects of temperature on concentration

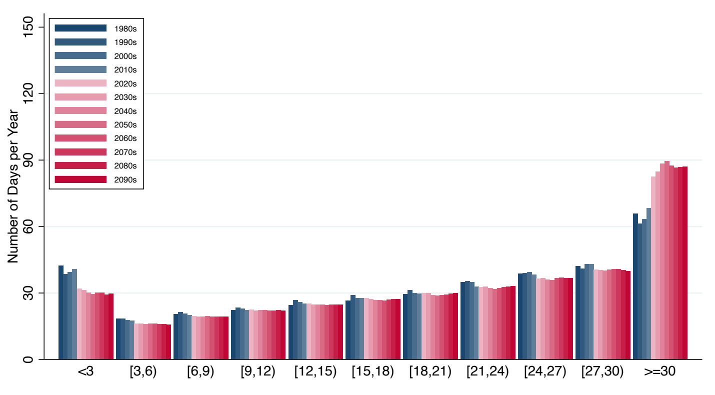
Dep. Var.	Δ Fraction of Emp. in Top 4 Largest Estab. (1)	Δ Log(HHI_Emp.) (2)
Panel A: Aggregate effect		
Δ Degree-Days > 18°C	0.0053*	0.0334**
	(0.0030)	(0.0150)
Panel B: Interacted with above-median indicator of electricity prices		
Δ Degree-Days > 18°C	-0.0009	0.0111
	(0.0028)	(0.0143)
Δ Degree-Days > 18°C × above median	0.0134***	0.0482**
	(0.0029)	(0.0185)
Panel C: Interacted with above-median indicators of electricity management participation		
Δ Degree-Days > 18°C	0.0107**	0.0422**
	(0.0050)	(0.0193)
Δ Degree-Days > 18°C × above median	-0.0111*	-0.0181
	(0.0056)	(0.0216)
Panel D: Interacted with above-median indicator of # of branches per 1000 people		
Δ Degree-Days > 18°C	0.0062	0.0440**
	(0.0037)	(0.0196)
Δ Degree-Days > 18°C × above median	-0.0013	-0.0220
	(0.0038)	(0.0183)
Panel E: Interacted with above-median indicator of frac. of small plants that are multi-unit		
Δ Degree-Days > 18°C	0.0069**	0.0569***
	(0.0033)	(0.0150)
Δ Degree-Days > 18°C × above median	-0.0030	-0.0493***
	(0.0024)	(0.0126)
Observations	11000	11000
Census Division FE	yes	yes
Commuting zone controls	yes	yes

Notes: The table shows the main coefficients when estimating the commuting-zone-industry-level long-run specification described in equation (2) to examine the long-run implications of temperature on local manufacturing activity. Δ Degree-Days > 18°C is divided by 100 for readability. In column (1), the left-hand side variable is the change in the natural logarithm of the fraction of employment in the top 4 largest establishment between the 2010s and the 1980s. In column (2), the left-hand side variable is the change in the natural logarithm of the average yearly Herfindahl-Hirschman Index between the 2010s and the 1980s, constructed on the basis of the number of employees reported by establishments. Panel A shows baseline results for changes in average CDDs between the 2010s and the 1980s. Panels B-E are augmented by additional interaction terms. In Panel B, the interaction term is an indicator for NAICS3-Census Regions with above-median electricity prices in 1998. In Panel B, the interaction term is an indicator for NAICS3 industries with above-median electricity management practice participation rates in 1998. In Panel C, the interaction term is an indicator for commuting zones with above-median number of branches per 1000 population in 1994. In Panel D, the interaction term is an indicator for NAICS3-commuting zones with an above-median fraction of small plants that are part of a multi-unit firm in the 1980s. Small firms are defined as firms in the smallest size quintiole (by number of empoyees) in the 1980s. Census Division fixed effects, NAICS-3 fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the commuting-zone level are included throughout. All columns further include commuting-zone-level controls for percentage of population that attended at least one year of college in 1980, log-transformed population in 1980, log-transformed income per capita in 1980, change in exposure to the China shock between 1990 and 2007, and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

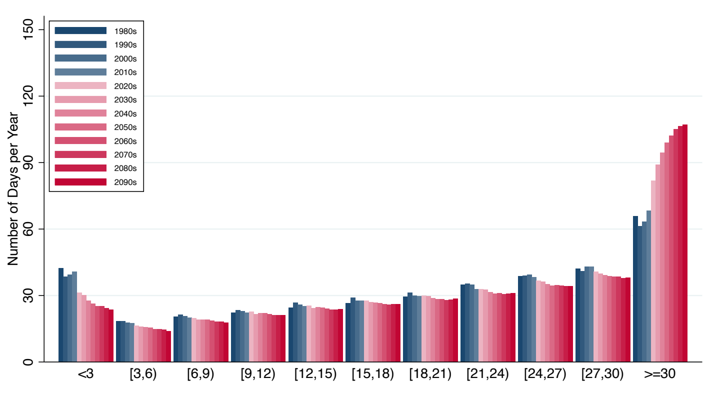
Internet Appendix

Figure A.1: Distribution of max temperature days by bin over time

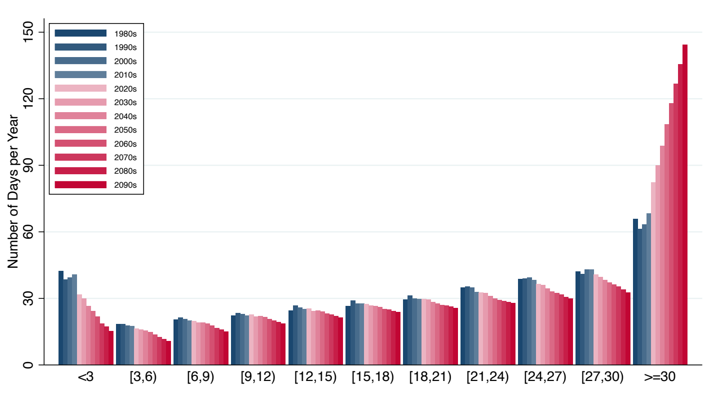
Panel A: Stringent Scenario (RCP 2.6)



Panel B: Intermediate Scenario (RCP 4.5)



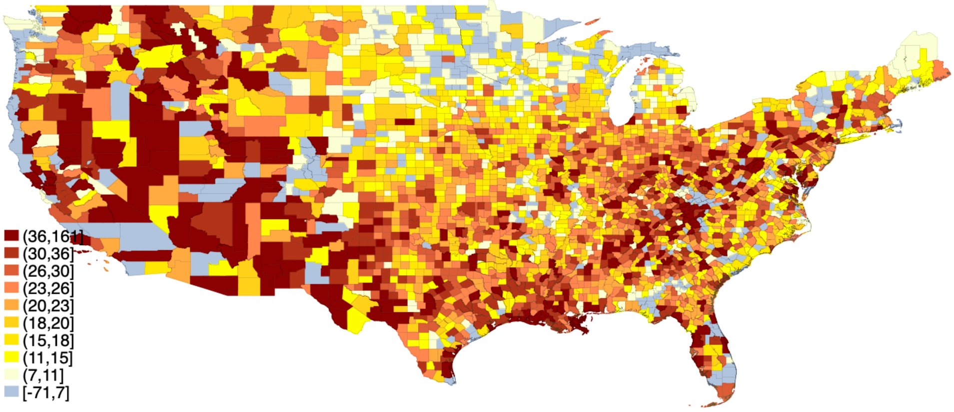
Panel C: High Greenhouse Gas Emission Scenario (RCP 8.5)



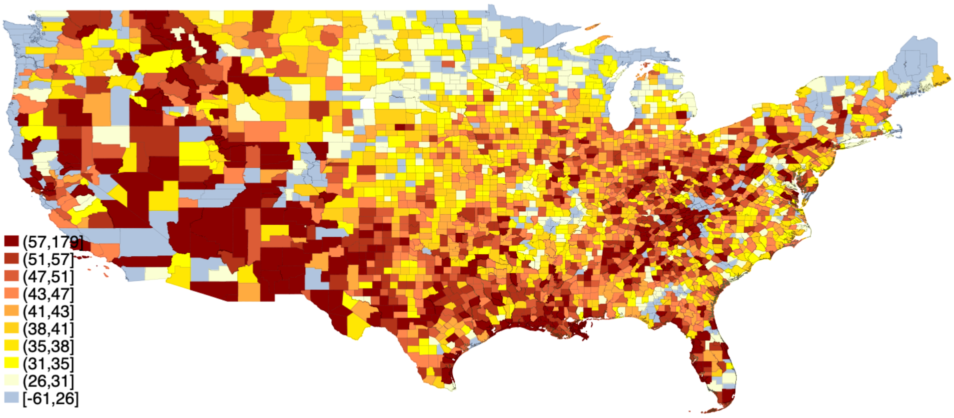
Notes: The figure shows decadal U.S. long-run temperature projections on the basis of big data generated by Hsiang et al. (2017) for the 1980s to 2090s. The underlying data are based on 44 climate models. Shown are projections under three different Representative Concentration Pathways (RCPs) used to describe scenarios of greenhouse gas (GHG) emissions and atmospheric concentrations: a stringent mitigation scenario (Panel A, RCP 2.6), an intermediate scenario (Panel B, RCP 4.5), and a scenario with very high GHG emissions (Panel C, RCP 8.5). Each bar shows the average annual number of days whose maximum temperature falls within a certain 3°C bins (x-axis) for a range of decades (color-coded bar), averaged across U.S. counties.

Figure A.2: Projected changes in the number of days above 29°C between the 1980s and the 2090s

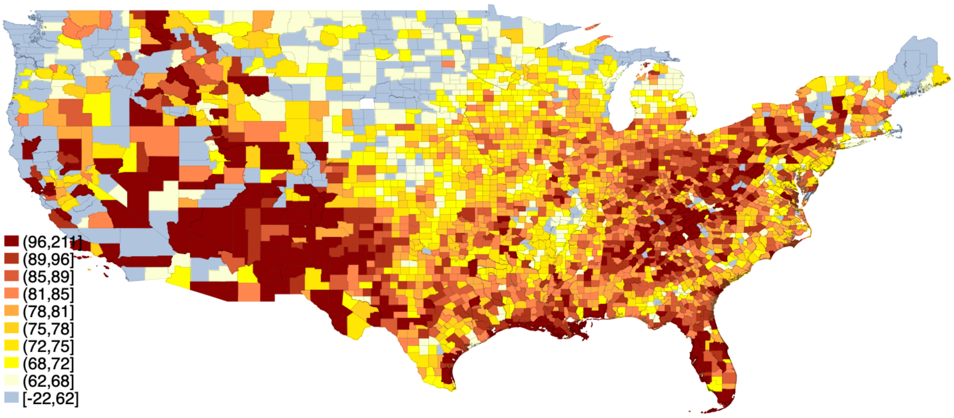
Panel A: Stringent Scenario (RCP 2.6)



Panel B: Intermediate Scenario (RCP 4.5)

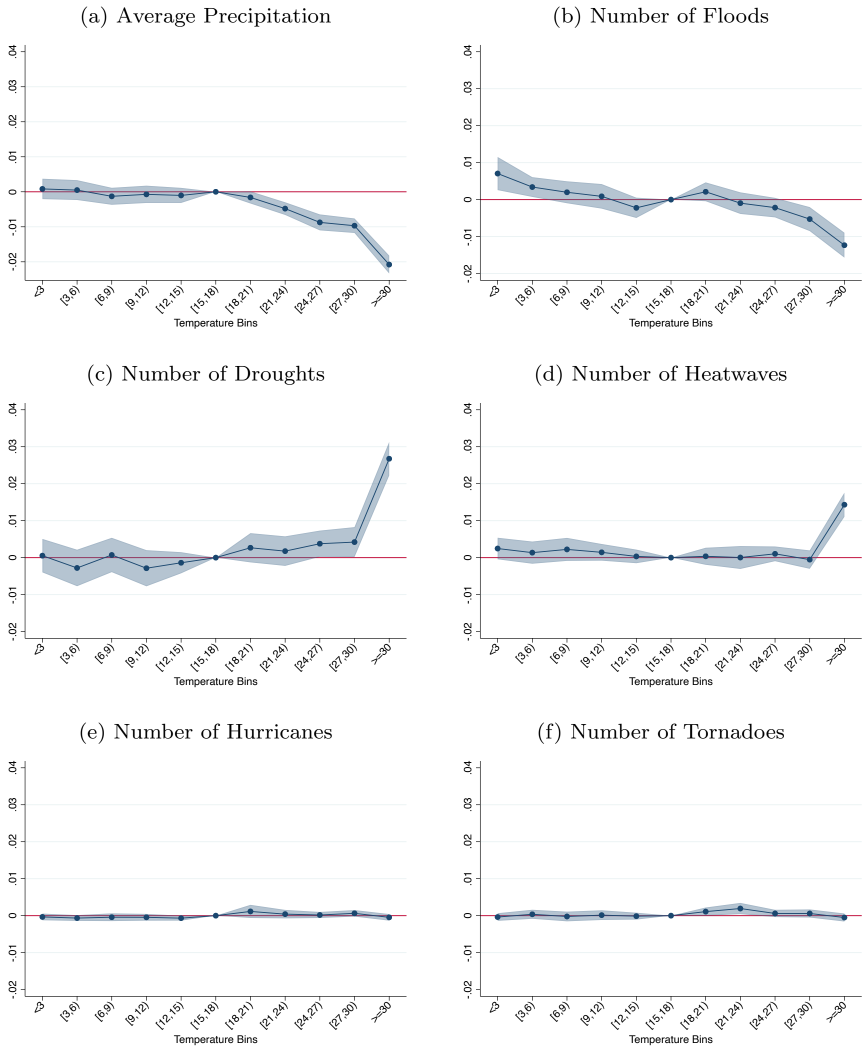


Panel C: High Greenhouse Gas Emission Scenario (RCP 8.5)



Notes: The figure shows long-run temperature projections by U.S. county for the contiguous 48 states on the basis of big data generated by Hsiang et al. (2017) for the 1980s to 2090s. The underlying data are based on 44 climate models. Shown is the county-level change between the average projected number of days above 29°C in the 2090s and the average number of days above 29°C in the 1980s for a stringent mitigation scenario (Panel A), an intermediate scenario (Panel B), and a scenario with very high GHG emissions (Panel C).

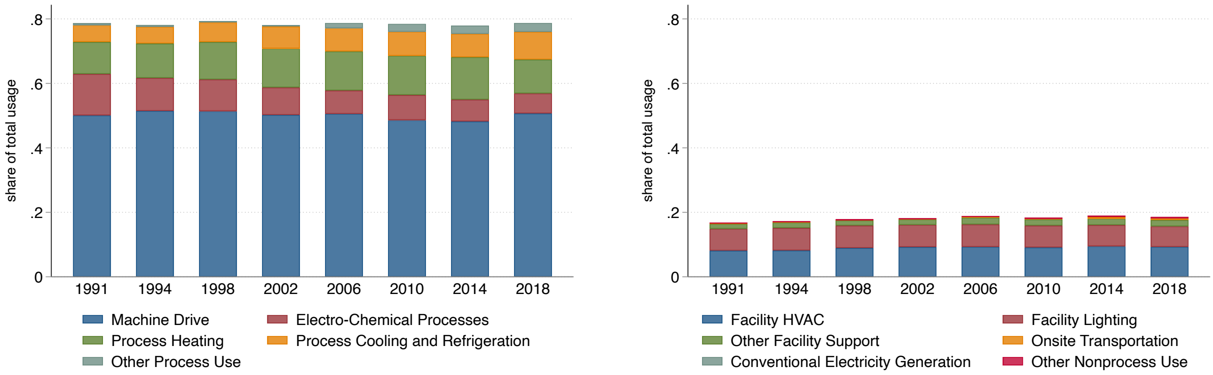
Figure A.3: Effects of long-run changes in temperature on precipitation and extreme weather events



Notes: The figure shows the point estimates and the 95% confidence interval of county-year level regressions of average precipitation (Panel a), number of floods (Panel b), number of droughts (Panel c), number of heatwaves (Panel d), number of hurricanes (Panel e), and number of tornados (Panel f) on the number of days in various temperature bins (x-axis), county fixed effects, and year fixed effects. Standard errors are clustered at the state level. Event data are from SHELDUS, while the temperature and precipitation data are from the PRISM Climate Group (we use the cleaned version of that data provided on Wolfram Schlenker's homepage).

FIGURE A.4: ELECTRICITY USAGE BY U.S. MANUFACTURING PLANTS

(a) production process (b) non-production process

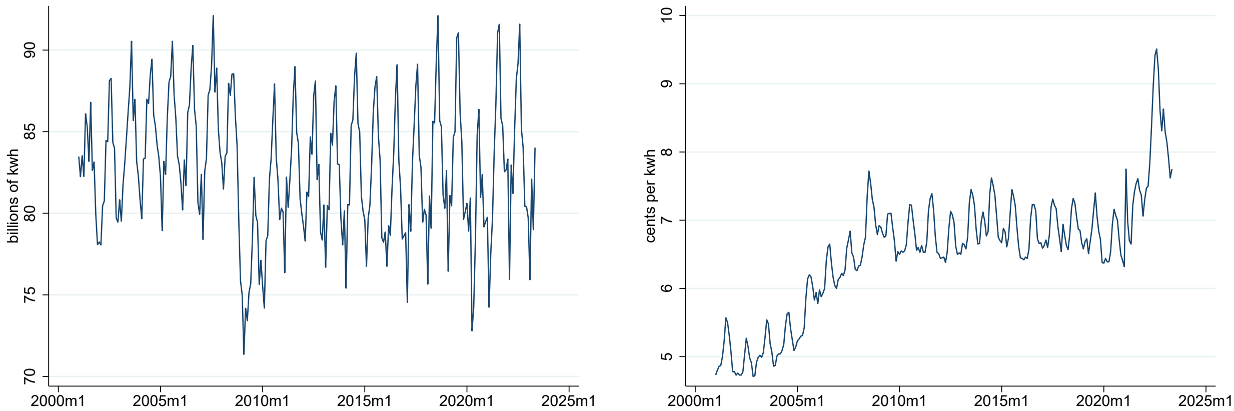


Notes: Data source: Manufacturing Energy Consumption Survey, all waves.

Figure A.5: Seasonality in industrial electricity demand and prices

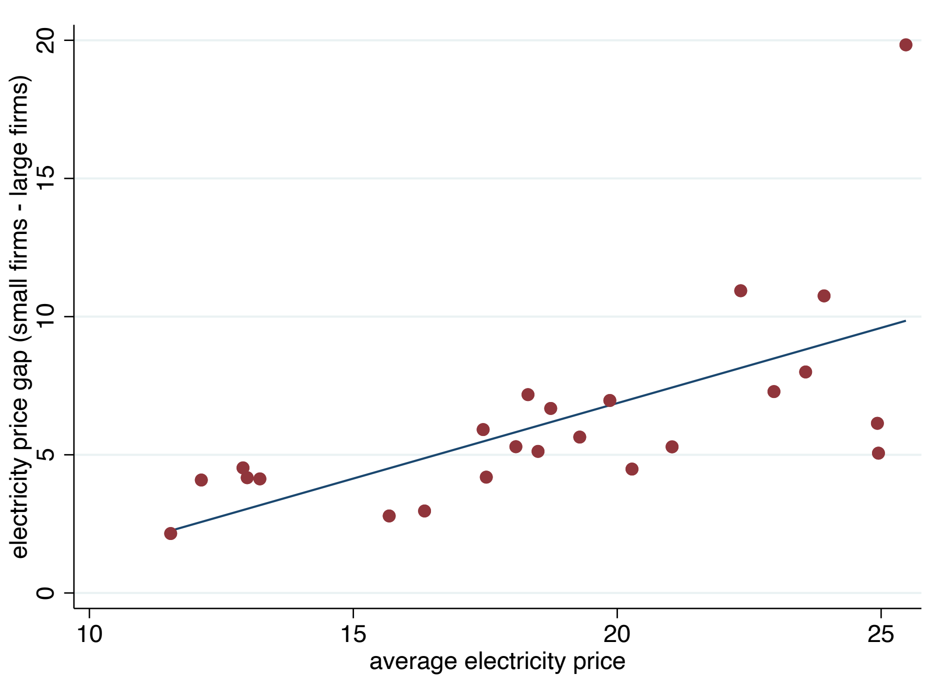
(a) Electricity sales, industrial sector

(b) Electricity prices, industrial sector



Notes: Data source: U.S. Energy Information Administration, Electric Power Monthly dataset available (`https://www.eia.gov/electricity/data.php`).

Figure A.6: Correlation between average electricity price and the price gap between small and large plants



Notes: The figure shows the positive correlation between the average electricity price and the price gap between small and large plants at the Census-Region-year level. The x-axis is the average electricity price in a Census-Region-year, and the y-axis is the price gap between the average prices for plants with an employment under 50 people and those for larger plants.

Table A.1: Variable Definitions

Variable	Definition	Source
Panel A: ASM & CMF Sample		
Energy Costs / TVS	The ratio of energy costs to total value of shipments.	
Electricity Costs / TVS	The ratio of electricity costs to total value of shipments.	
Log(TFP)	Log of total factor productivity.	
Log(Value-Added/Total Hours Worked)	Log of the ratio of value-added to workers' total working hours.	
Log(Total Hours Worked)	Log of workers' total working hours.	
Log(TVS)	Log of total value of shipments.	
Panel B: LBD Sample		
Exit	An indicator of exit, where employment of the firm in year t is above-zero and in year t+1 is zero.	
Panel C: LBD - Long-run difference between the 1980s and the 2010s		
Δ Degree-Days > 18 °C	long-difference in the average degree days above 18 °C from 1980s to 2010s.	
Δ Degree-Days < 18 °C	long-difference in the average degree days below 18 °C from 1980s to 2010s.	
Δ Log(# Establishments)	Long-difference in log of average total establishment from 1980s to 2010s.	
Δ Log(Employment)	Long-difference in log of average total employment from 1980s to 2010s.	
Δ Log(Avg. Size of Establishments)	long-difference in log of average employment size from 1980s to 2010s.	
Δ Frac. of Emp. in Top 5 Largest Estab.	long-difference in the average fraction of employment from top 5 establishments from 1980s to 2010s.	
Δ Log(HHI_Emp.)	long-difference in the average HHI of employment from 1980s to 2010s.	
Panel D: Control Variables from Other Sources		
Avg. Precipitation	Average daily precipitation of a location-year.	Database built by Wolfram Schlenker
# Events of Floods	Number of drought events in the county-year.	SHEDULS from Arizona State University
# Events of Droughts	Number of drought events in the county-year.	SHEDULS from Arizona State University
# Events of Heatwaves	Number of heatwave events in the county-year.	SHEDULS from Arizona State University
# Events of Hurricane	Number of hurricane events in the county-year.	SHEDULS from Arizona State University
# Events of Tornado	Number of tornado events in the county-year.	SHEDULS from Arizona State University
Δ IPW	Changes in the exposure to the import shock from China from 1990 to 2007.	Autor, Dorn, and Hanson (2013)
Perc. of college students	Percentage of 25-year old or above population finished at least one year of college.	US Census
Log(Population)	Log of county population.	Database built by Andrew Leuven
Log(Income pc)	Log of county per capita income.	IPUSM

Table A.2: Short-run effects of temperature on productivity: Alternative measure of productivity removing energy costs

	$\text{Log}(\frac{\text{value added w/out energy costs}}{\text{total working hours}})$	
	(1)	(2)
T < 3°C	-0.0155	-0.0177
	(0.0214)	(0.0319)
3°C ≤ T < 6°C	-0.0307	-0.0467
	(0.0186)	(0.0300)
6°C ≤ T < 9°C	0.0104	-0.0034
	(0.0214)	(0.0266)
9°C ≤ T < 12°C	-0.0009	-0.0004
	(0.0181)	(0.0230)
12°C ≤ T < 15°C	0.0096	0.003
	(0.0168)	(0.0192)
18°C ≤ T < 21°C	-0.0151	-0.0302
	(0.0186)	(0.0213)
21°C ≤ T < 24°C	-0.0277	-0.0477**
	(0.0186)	(0.0228)
24°C ≤ T < 27°C	-0.0266	-0.0501**
	(0.0175)	(0.0207)
27°C ≤ T < 30°C	-0.0455***	-0.0609***
	(0.0168)	(0.0204)
T ≥ 30°C	-0.0441***	-0.0729***
	(0.0150)	(0.0185)
Observations	1922000	1922000
R-squared	0.792	0.793
Establishment FE	yes	yes
NAICS3-Year FE	yes	yes
Extreme weather controls	yes	yes
Census Division-year FE	yes	
State-year FE		yes

Notes: In this table, we replicate the results presented in Table 4 Columns 3-4, removing energy costs from the numerator used to calculate productivity. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.3: Short-run effect of temperature on size and exit

	Log(TVS) (1)	Exit (2)
T < 3°C	0.0631	-0.0025
	(0.0424)	(0.0061)
3°C ≤ T < 6°C	0.0343	-0.0021
	(0.0344)	(0.0054)
6°C ≤ T < 9°C	0.0193	0.0023
	(0.0322)	(0.0043)
9°C ≤ T < 12°C	-0.0228	0.0028
	(0.0201)	(0.0044)
12°C ≤ T < 15°C	0.0062	0.004
	(0.0155)	(0.0036)
18°C ≤ T < 21°C	-0.0105	-0.0018
	(0.0158)	(0.0020)
21°C ≤ T < 24°C	-0.0051	0.001
	(0.0163)	(0.0024)
24°C ≤ T < 27°C	-0.0047	0.0016
	(0.0215)	(0.0023)
27°C ≤ T < 30°C	0.002	0.0031
	(0.0230)	(0.0028)
T ≥ 30°C	0.0103	0.0033
	(0.0211)	(0.0029)
Observations	1922000	13590000
R-squared	0.953	0.015
Zipcode FE		yes
Establishment FE	yes	
NAICS3-Year FE	yes	yes
Extreme weather controls	yes	yes
State-year FE	yes	yes

Notes: The table uses the panel data approach described in equation (1) to estimate the short-run effect of temperature on the total value of shipments (Column 1) and exit (Column 2). Exit is an indicator variable set equal to one if a plant had strictly more than zero employees in year t and zero employees in year t+1. The analysis is at the plant-year level and the sample period comprises 1977-2018. The shown coefficients of interest represent the number of days with maximum temperature in each respective temperature bin (β_b in Equation (1)) in a given year in a plant's zip code. The number of days in a temperature bin is divided by 100 for readability and the temperature bin [15°C,18°C) is used as the reference bin and therefore omitted. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.4: Short-run effects of temperature on energy costs and productivity: Robustness to High Tradability Manufacturing

	Energy Costs/TVS		Log(TFP)	
	(1)	(2)	(3)	(4)
T < 3°C	0.0234	-0.1311	-0.0225	-0.0307
	(0.0908)	(0.1592)	(0.0176)	(0.0237)
3°C ≤ T < 6°C	0.1373	0.0695	-0.0496**	-0.0415
	(0.0847)	(0.1035)	(0.0236)	(0.0330)
6°C ≤ T < 9°C	0.1642*	0.1546	-0.0284	-0.0388
	(0.0832)	(0.1204)	(0.0213)	(0.0255)
9°C ≤ T < 12°C	0.0433	0.095	-0.0291	-0.0343
	(0.0719)	(0.0861)	(0.0180)	(0.0205)
12°C ≤ T < 15°C	0.1294**	0.1443*	-0.0201	-0.0244
	(0.0583)	(0.0736)	(0.0198)	(0.0204)
18°C ≤ T < 21°C	0.09	0.1223	-0.0373*	-0.0476**
	(0.0989)	(0.1207)	(0.0196)	(0.0205)
21°C ≤ T < 24°C	0.0683	0.1012	-0.0583***	-0.0790***
	(0.0838)	(0.1027)	(0.0188)	(0.0220)
24°C ≤ T < 27°C	0.1812***	0.2564**	-0.0504***	-0.0727***
	(0.0670)	(0.1093)	(0.0162)	(0.0207)
27°C ≤ T < 30°C	0.2168***	0.3393***	-0.0597***	-0.0844***
	(0.0613)	(0.1030)	(0.0171)	(0.0209)
T ≥ 30°C	0.1730**	0.3439***	-0.0570***	-0.0918***
	(0.0756)	(0.1218)	(0.0152)	(0.0211)
Observations	975000	975000	975000	975000
R-squared	0.823	0.824	0.784	0.786
Establishment FE	yes	yes	yes	yes
NAICS3-Year FE	yes	yes	yes	yes
Extreme weather controls	yes	yes	yes	yes
Census Division-year FE	yes		yes	
State-year FE		yes		yes

Notes: In this table, we replicate the results presented in Tables 3 and 4 (Colmns 1-2), restricting the sample to tradable manufacturing sectors. Tradable manufacturing sectors are those with an above median geographical concentration index, as proposed by Mian and Sufi (2014). All specifications control for average ZIP Code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.5: Short-run effects of temperature on energy costs and productivity: Robustness to excluding sectors dependent on Agriculture via input-output linkages

	Energy Costs/TVS		Log(TFP)	
	(1)	(2)	(3)	(4)
T < 3°C	0.0033	-0.0138	0.0046	0.0183
	(0.0789)	(0.1375)	(0.0156)	(0.0240)
3°C ≤ T < 6°C	0.1267*	0.1013	-0.0173	-0.0112
	(0.0706)	(0.1230)	(0.0184)	(0.0229)
6°C ≤ T < 9°C	0.0311	0.0631	-0.0004	0.0001
	(0.0721)	(0.0866)	(0.0140)	(0.0207)
9°C ≤ T < 12°C	0.1021	0.0768	-0.0057	0.0025
	(0.0795)	(0.1049)	(0.0123)	(0.0154)
12°C ≤ T < 15°C	0.0676	0.1191*	-0.0102	-0.0097
	(0.0529)	(0.0604)	(0.0163)	(0.0210)
18°C ≤ T < 21°C	0.0724	0.0747	-0.0107	-0.0197
	(0.0536)	(0.0680)	(0.0122)	(0.0158)
21°C ≤ T < 24°C	0.1424**	0.1377*	-0.0252*	-0.0430**
	(0.0629)	(0.0758)	(0.0133)	(0.0188)
24°C ≤ T < 27°C	0.1326***	0.1594**	-0.0156	-0.0349*
	(0.0493)	(0.0727)	(0.0121)	(0.0182)
27°C ≤ T < 30°C	0.1590***	0.2263***	-0.0314**	-0.0437**
	(0.0523)	(0.0650)	(0.0118)	(0.0164)
T ≥ 30°C	0.1720**	0.2451***	-0.0295**	-0.0542***
	(0.0654)	(0.0894)	(0.0112)	(0.0177)
Observations	1715000	1715000	1715000	1715000
R-squared	0.792	0.793	0.76	0.762
Establishment FE	yes	yes	yes	yes
NAICS3-Year FE	yes	yes	yes	yes
Extreme weather controls				
Census Division-year FE	yes		yes	
State-year FE		yes		yes

Notes: In this table, we replicate the results presented in Tables 3 and 4 (Columns 1-2), excluding from our sample manufacturing sectors related to food processing, beverages and tobacco, for which expenditure in agricultural inputs constitute more than 5% of the value of production according to the 1980 Input-Output Tables of the BEA. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.6: Short-run effects of temperature on energy costs and productivity: Robustness to alternative temperature definitions

	Energy Costs/TVS	Log(TFP)
	(1)	(2)
Panel A: Mean temperature bins		
T < -3°C	0.0196	0.0272
	(0.1595)	(0.0291)
-3°C ≤ T < 0°C	-0.0785	0.0071
	(0.1113)	(0.0223)
0°C ≤ T < 3°C	0.054	-0.0087
	(0.0933)	(0.0169)
3°C ≤ T < 6°C	0.0293	0.0081
	(0.0676)	(0.0127)
6°C ≤ T < 9°C	0.0575	0.006
	(0.0912)	(0.0127)
12°C ≤ T < 15°C	-0.0105	-0.0044
	(0.0743)	(0.0101)
15°C ≤ T < 18°C	0.0592	-0.0330***
	(0.0925)	(0.0106)
18°C ≤ T < 21°C	0.1539**	-0.0379*
	(0.0742)	(0.0217)
21°C ≤ T < 24°C	0.2034**	-0.0588***
	(0.0774)	(0.0162)
T ≥ 24°C	0.2579**	-0.0572***
	(0.0986)	(0.0178)
Panel B: Degree-Days		
Degree-Days > 18°C	0.0139***	-0.0017*
	(0.0049)	(0.0009)
Degree-Days < 18°C	-0.0002	0.0018
	(0.0074)	(0.0012)
Observations	1922000	1922000
Establishment FE	yes	yes
NAICS3-Year FE	yes	yes
State-year FE	yes	yes

Notes: In this table, we replicate the results presented in Tables 3 and 4 (Columns 1-2), using the daily average temperature (as opposed to the daily maximum temperature) to construct temperature bins. The number of days in a temperature bin is divided by 100 for readability and in this specficiation, the temperature bin [9°C,12°C) is used as the reference bin and therefore omitted. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.