Temperature, Adaptation, and Local Industry Concentration*

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Abstract

We use four decades of plant-level data from the U.S. Census to study the effects of temperature on manufacturing activity. In the short run, high-temperature shocks increase energy costs and reduce productivity for small plants, while large plants are mostly unaffected. In the long run, commuting zones that experience larger temperature increases see a decline in the number of small plants, a reallocation of labor from small to large plants, and higher industry concentration. We explore mechanisms that may explain why large plants adapt better to climate change, including differences in energy prices, managerial skills, and access to finance.

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 rose substantially over the 20th century and are projected to continue increasing (Masson-Delmotte et al., 2021). In the continental United States, the median county-level temperature rose by 0.6°C from the 1980s to the 2010s. Even under optimistic climate mitigation scenarios, the average county-level number of days with maximum temperature above 30°C is projected to increase from 60 in the 2010s to 90 by the end of this century. This warming trend has direct implications for manufacturing operations, particularly through its effects on energy expenditures (which represent 26% of profits for U.S. manufacturing plants) and on productivity. Given that the manufacturing sector accounts for 10.3% of U.S. GDP and employs 12.6 millions workers (BEA, 2023), quantifying these effects is central for assessing the broader economic consequences of climate change in advanced economies.

In this paper, we provide comprehensive evidence on how temperature shapes U.S. manufacturing activity in both the short and long run. Leveraging four decades of establishment-level data from the U.S. Census Bureau, we analyze three key dimensions of this relationship. First, we quantify the effects of temperature shocks on plant-level energy costs and productivity, providing direct evidence on the channels through which temperature affects manufacturing operations. Second, we study heterogeneous responses across the plant size distribution, recognizing that adaptation capabilities may vary systematically with plant characteristics. Third, we trace the long-run impact of changes in climate on local industrial structure, investigating whether sustained temperature increases lead to reallocation of manufacturing activity across plants with different adaptation capabilities.

To study these questions, we employ two complementary empirical strategies used in environmental economics (Burke and Emerick 2016, Heutel et al. 2021). The first strategy captures the contemporaneous response of manufacturing outcomes to additional days in certain temperature bins in a given year. This allows us to quantify how additional high-temperature days affect plant-level outcomes such as energy costs and productivity. The

second strategy adopts a long-run perspective, relating changes in average temperatures experienced by U.S. commuting zones (CZs) over the last four decades to long-run shifts in manufacturing activity. Together, these approaches enable us to document both the immediate operational impacts of temperature shocks and the deeper structural adjustments that follow from persistent climate change.

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 (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 capture 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.

Temperatures can affect energy costs for both production processes (e.g. operating machinery, cooling, refrigerating or heating inputs) and non-production processes (e.g. facility temperature control and lighting). We document that expenditures in electricity and fuel respond significantly to contemporaneous temperature shocks. The estimates indicate that plants exposed to a one-standard-deviation higher number of hot days – which we define as days with maximum temperature equal or above 30°C – experience a 4.6% higher increase in energy costs, while we find no significant effects for variation in cold days.

We also document that higher-than-usual temperatures lead to lower productivity, measured as value added per worker or total factor productivity (TFP). These results are not mechanically driven by higher energy costs, as we find similar effects when constructing productivity measures that do not include energy as an input. The estimates indicate that plants exposed to a one-standard-deviation higher number of hot days experience declines in productivity of 2.7% (TFP) to 3.5% (value added per worker).

Existing work on the impact of temperature on the productivity of U.S. establishments has focused on plants owned by publicly listed firms and operating across all sectors, documenting small and statistically insignificant effects on sales and productivity (Addoum et al., 2020). This result holds also in our data when restricting the sample to manufacturing plants owned by public firms. However, over 95% of U.S. manufacturing plants in the U.S. Census are owned by private firms. Extending the analysis to plants of private firms shows that temperature shocks significantly reduce the productivity of the average U.S. manufacturing plant.

Consistent with this result, when exploring the heterogeneous impact of temperature shocks across the plant size distribution, we find that the negative effects on productivity and the positive effects on energy costs are concentrated among small and medium plants, while large plants are mostly unaffected.

Temperature shocks might affect local demand in less tradable manufacturing sectors, or might affect manufacturing production via input-output linkages with local agriculture. 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. Our results are also robust to alternative temperature measures, such as average rather than maximum temperature.

Despite the documented effects on costs and productivity, we observe no significant contemporaneous response via down-scaling or exiting a given location by affected plants. Indeed, it is plausible that key industrial decisions, such as exiting a given market, are not driven by abnormal temperature shocks, especially if such shocks are interpreted as idiosyncratic and therefore likely to revert to normal in the following years.

In the second part of the paper, we 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 the 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 Census 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. The decline in the number of plants is driven by a reduction in small plants, while we find no differential change in the number of large plants. Average size of manufacturing plants as measured by number of workers increases by 6% for one standard deviation higher increase in temperature at the commuting zone level. These effects are consistent with a reallocation of workers from small to large plants in areas that got warmer at a faster pace over the last four decades.

Consistent with this reallocation process, we 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 60 Cooling Degree Days, or CDDs, above 18°C per year) saw a 0.5 percentage points larger increase in the share of employment concentrated in the top 5 largest plants and a 3% larger increase in the Herfindahl-Hirschman Index (HHI).[1]

These findings suggest that large manufacturing plants might be better equipped for long-run adaptation to climate change than small ones. We discuss and test potential mechanisms that are consistent with 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. To test this mechanism, we interact long-run changes in temperature at the CZ level with electricity prices (dollars per unit of energy) sourced from MECS. We document that the effect of higher temperatures on concentration

[1]A Cooling Degree Day (CDD) is the difference in degrees between average daily temperature and 18°C conditional on the average daily temperature being above 18°C. Yearly CDD is the sum of all daily CDDs in a given year.

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 energy management practices sourced from the MECS. Consistent with this mechanism, we find that higher participation rates in energy management practices lead 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. The evidence is consistent with access to external finance favoring firm adaptation to long-run changes in temperatures, although estimates are too noisy to draw strong conclusions on the role of this mechanism.

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 discussion of outcomes studied and methods employed in the literature). Existing studies have mostly focused on documenting the adverse effects of weather shocks and climate change on output and productivity in developing economies, which are, 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).[2]

[2]A notable exception are studies of the agricultural sector in developed economies. Here, short-term temperature shocks are generally found to have adverse effects on agricultural productivity. 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, Auffhammer et al. (2006) and Gupta et al. (2017) for evidence on India. In addition, Deryugina and Hsiang (2014) show

Our work builds on a growing literature examining the effects of temperature on firm-level outcomes. Part of this literature has focused on U.S. data. For example, Addoum et al. (2020) document that higher temperatures do not significantly affect the short-run sales and productivity of establishments owned by U.S. public firms, Addoum et al. (2023) show that earnings of U.S. public firms across more than 40% of industries do respond to temperature extremes, and Acharya et al. (2022) show that higher temperatures lead to higher bond yields and expected returns for equity. International evidence includes Zhang et al. (2018), which shows that Chinese manufacturing firms exhibit an inverted U-shape relation between temperature and total factor productivity, and Pankratz et al. (2023), which examines data from 93 countries and documents that increased exposure to extremely high temperatures reduces firms' revenues and operating income.[3] We contribute to this literature by providing direct micro-level evidence on the effect of temperature shocks on energy costs in manufacturing plants, by extending the analysis of temperature impacts on productivity to plants of private manufacturing firms in the U.S., and by documenting the heterogeneous effects on energy costs and productivity across the plant size distribution. We also investigate the long-run implications of the differential impact of temperature on small versus large plants.

Our results are also relevant to the literature on adaptation. This body of work has shown that more productive firms – which also contribute disproportionally to overall industry productivity – have stronger incentives to adapt to climate change (Somanathan et al. 2021, Zivin and Kahn 2016; see Samuelson 1947 and Viner 1958 for the theoretical foundations). For instance, clients with multiple suppliers dynamically reconfigure their supplier network in response to weather shocks (Custodio et al. 2022, Pankratz and Schiller 2024). Similarly, heat waves trigger geographic reallocation of production toward unaffected locations among multi-location firms, while standalone firms tend to downsize under similar shocks (Acharya et al. 2023, Castro-Vincenzi 2022).

that temperature affects income even in the U.S.

[3]Focusing on Italian firms, Chiavari et al. (2024) present a general equilibrium 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.

Firms employing outdoor labor also respond to extreme temperatures and heat-related regulation by substituting labor with capital (Xiao 2023). We contribute to this literature by documenting that large manufacturing plants adapt more effectively to long-term climate change than smaller plants, and by identifying two novel channels underlying this adaptive advantage: lower electricity prices and higher managerial quality.

Finally, our findings are informative for the large literature on industry concentration (De Loecker et al. 2020, Grullon et al. 2019, Covarrubias et al. 2020, Kwon et al. 2024). Drivers behind the increase in industry concentration observed in the U.S. over the last decades 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), the increasing importance of globalization (Feenstra and Weinstein 2017), and the shift away from physical to intangible capital (Alexander and Eberly 2018, Crouzet and Eberly 2023). 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.

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. Section III describes the identification strategy used to estimate the short-run effects of temperature shocks on plant-level outcomes, and the corresponding results. Section IV describes the identification strategy used to estimate the impact of long-run changes in temperatures over the last four decades on communing-zone level outcomes, presents the corresponding results and discusses potential mechanisms.

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 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.[4] 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, output (measured by value of shipments), energy costs, 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.

Second, 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, as well as employment counts, which we use to measure establishment size. We have access to LBD data for the 1977 to 2019 period. To distinguish establishments owned by public versus private firms, we rely on the Census-provided GVKEY bridge.

Weather Data. We use two data sources to capture weather shocks and temperature-related changes in climate. 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

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

Wolfram Schlenker's homepage.[5] The data include the daily minimum and maximum temperatures for 2.5-mile by 2.5-mile grids on the basis of a constant set of weather stations over the 1950-2019 sample period. This ensures that the resulting time series of temperatures does not vary due to the opening or closing of weather 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 and Cooling Degree Days ($CDDs$).

We use data on extreme weather events, such as droughts, floods, heatwaves, hurricanes and tornadoes from the Spatial Hazard Events and Losses Database for the United States (SHELDUS).[6] 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 data provided by alternative 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

[5]For details such as treatment of missing values and selection of underlying stations, please refer to: `https://wolfram-schlenker.info/links.html`.

[6]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`.

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 energy 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.

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

The contiguous U.S. has experienced substantial increases in average temperature over the past century. According to the climatology literature described in the Masson-Delmotte et al. (2021) report, the significant emergence of changes in temperature relative to historical averages occurred in North America after 1981.[7] Figure A.1 shows the dynamics of annual average surface temperature anomalies across the contiguous 48 states over the 1900 to 2019 period. A temperature anomaly is the difference between the average annual temperature and the average temperature over the 1901 to 2000 period. Figure A.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 Masson-Delmotte et al. (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.2, 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.

[7] See Masson-Delmotte et al. (2021), p. 133. Historical climate averages are calculated using temperature data for the baseline period from 1850 to 1900.

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).[8] 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.2 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 about 90 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).

III Short-run Effects

We employ two approaches to estimate the effect of temperature on manufacturing outcomes. In this section, we describe our first approach – the panel approach – which is designed to capture the contemporaneous response of manufacturing outcomes to short-term (yearly) temperature shocks and present the corresponding results. Our second approach – the long differences approach – is described in section IV.[9]

[8] 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, from [3°C,6°C) to [27°C,30°C), plus two additional bins capturing average daily temperatures strictly below 3°C and weakly above 30°C.

[9] 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.

III.A Identification strategy

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 allows for arbitrary non-linear relationships between temperature and outcome variables.[10] 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) as the omitted benchmark. 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.[11] In addition, when examining outcome variables obtained from ASM/CMF (i.e., energy costs, productivity), 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 include

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

[11] 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.

additional fixed effects to absorb potential time-varying industry and geographic dynamics that might confound our key estimates. Specifically, throughout, we 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 further include Census Division fixed effects interacted with year fixed effects and, in an alternative specification, State fixed effects 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, namely hurricanes and tornadoes.

III.B Results

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.

III.B.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. 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 U.S. manufacturing firms of 8.4%, energy costs may represent on average about 26% of profits.[12] The results are reported in Table 2 columns (1)-(2) and visualized in Figure 1 (a). The point estimates should be interpreted as the effect of additional days in a given temperature bin relative to local average 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.[13] 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 2 we estimate equation (1) using as outcome variable electricity costs normalized by total value of production. The results are also visualized in Figure 1 (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

[12] According to the 2024 Q3 U.S. Census Quarterly Financial Report, between 2003 Q1 to 2024 Q3, the average profit per dollar of sales for the manufacturing sector is 8.4% after tax.

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

being less seasonal than residential or commercial energy consumption – industrial energy 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 industrial 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.[14] 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, divide the plant size distribution into quintiles, and categorize large plants as those in the top quintile of the employment distribution and small plants as those in the bottom four quintiles in each industry-year. For perspective, plants in the top quintile employ 188 workers on average, while those in the bottom four quintiles employ 11. We show that the results are qualitatively and quantitatively similar if using alternative cutoffs to categorize large plants, such as those in the top quartile of the employment distribution.

To estimate the differential effect of temperature on the energy costs of small vs large plants, we estimate equation 1 within each subsample of plants (small vs large). Then, we test for statistical differences in the effects of temperature shocks across small vs large plants by running a pooled regression in which all covariates are interacted with a dummy capturing small plants.

The results are visualized in Figure 2. This figure reports both the estimated effects of temperature in the subsample of large plants, and the estimated differential effects of temperature on small plants relative to large plants. The estimates show that the

[14] 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.

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 plants (relative to no effect on large plants). These results are robust when we divide the plant size distribution into quartiles instead, and categorize large plants as those in the top quartile of the employment distribution and small plants as those in the bottom three quartiles (see Figure A.6).

There are several potential explanations for this result. First, large plants are more likely to obtain lower energy prices due to volume discounts, economies of scale, or stronger bargaining power, leading to overall lower energy costs (MCES, 2018). In addition, 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 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. Furthermore, 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.

III.B.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) using $log(TFP)$ as the outcome variables are reported in Table 3 columns (1)-(2) and plotted in Figure 3. 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). Point estimates should be interpreted as the effect of additional days in a given temperature bin relative to the omitted benchmark bin [15°C-18°C).

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 2.7% decline in TFP and a 3.5% decline in labor productivity.

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 check 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. 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.

These results are prima facie surprising given that prior research has documented small and statistically insignificant effects of temperature on sales and productivity in U.S. manufacturing plants (Addoum et al., 2020). A key distinction, however, is that earlier work focused on plants owned by publicly listed firms, whereas the Census data used in our analysis covers all plants, including those owned by private firms which account for over 95% of the U.S. manufacturing plant sample. This allows us to test for statistical differences between public- and private-firm plants using pooled regressions that include both types of plants and interact temperature bins with a private-firm-ownership dummy.

Figure A.7 presents the results. Panel (a) shows the estimated temperature effects for plants of publicly listed firms, while Panel (b) shows the differential effects for plants owned by private firms relative to public firms. Consistent with earlier studies, we find no systematic temperature effects on productivity for public-firm plants: point estimates are small and statistically insignificant across all temperature bins. By contrast, Panel (b) reveals negative and statistically significant interaction coefficients in the hottest temperature bins, indicating that higher temperatures lead to significant productivity losses for private-firm plants. Combined with our main results in Table 3 and Figure 3, this evidence highlights that including plants of private firms is crucial for understanding how temperature shocks affect productivity of the average U.S. manufacturing establishment.

Next, we explore heterogeneous effects across the plant size distribution, as in our analysis of energy costs. Note that public-firm ownership is highly correlated with plant size: plants owned by U.S. public firms employ an average of 343 workers, compared with

just 36 workers at plants owned by private firms. Figure 4 shows that temperature shocks have statistically insignificant effects on the productivity of large plants (top quintile), but they lead to large and significant productivity declines in small plants. The point estimates of the interaction terms confirm that productivity in small plants is significantly more adversely affected by high temperatures than productivity in large plants. This result is robust to using quartiles to identify large vs. small plants in the firm size distribution, as shown in Figure A.8.[15]

Differences in the type of labor and capital used by plants of different size can rationalize these heterogeneous effects. Larger plants may 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 discuss and provide evidence on mechanisms in section IV.C.

III.B.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 plant 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

[15]Notice that higher energy expenditure increases plant costs but might also help to partly absorb the impact of temperatures on productivity, for example if energy is used for temperature control in the facility. This relationship between energy expenditure and productivity is hard to test as we do not observe how manufacturing plants use energy. However, the evidence presented in Figures 2 and 4 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.

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.

III.B.4 Robustness Tests and Heterogeneity by Regions

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.

Further, 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 employ a continuous specification using Cooling Degree Days (CDD) and Heating Degree Days (HDD)–standard metrics used by meteorological and energy agencies to quantify temperature-related energy demand. CDD (HDD) is defined as the number of degrees by which the average daily temperature exceeds (falls below) 18°C, conditional on being above (below) this threshold. As shown, yearly changes in CDD have strong predictive power of both higher energy costs and lower productivity at the plant level, while we find no effect of cooler-than-usual temperature shocks (HDD).

Finally, we investigate whether temperature shocks have heterogeneous effects in the Northern vs Southern regions of the U.S. Overall, the results in Table A.7 show that the impact of temperature shocks on energy costs and productivity are similar in magnitude across both regions. Northern regions show more precisely estimated negative effects of high temperature shocks, while Southern regions exhibit larger and precisely estimated negative effects even for low temperature shocks, possibly due to being less accustomed to such shocks. Note that we are not able to estimate coefficients for the coldest temperature bins in the South, as most zip codes with manufacturing plants in this region almost never experience such temperature extremes.

IV Long-run Effects

The short-run responses to temperature shocks documented in Section III.B 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.

In this section, we describe the long differences approach, which 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). We present the corresponding results and discuss potential mechanisms.

IV.A Identification strategy

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 following Burke and Emerick (2016):

$$\Delta y_{c(d),2010s-1980s} = \alpha_d + \beta \Delta CDD_{c(d),2010s-1980s} + \lambda X_{c(d)} + u_{c(d)} \tag{2}$$

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 Census division d.[16] 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 due to data availability: the U.S. Census LBD data provide consistent coverage of manufacturing activity for the 1980 to 2019 period. 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).

In equation (2), we use Cooling Degree Days (CDD) as a continuous measure of temperature. CDD is standard measure designed to capture the energy required to keep

[16]The U.S. Census Bureau divides U.S. states into 9 Census 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.

temperature at a baseline level. Daily CDD is defined as the difference in degrees between the average daily temperature in a location and 18°C, which is the baseline temperature at which no cooling is necessary, conditional on the average daily temperature being above 18°C. If the average temperature falls below or equals 18°C, the CDD for that day is zero.[17] For each CZ, we compute CDD as the sum of all $CDDs$ over a year.[18]

Equation (2) includes census-division fixed effects, which implies that the relevant variation originates 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 5 and Appendix Figure A.9.

Figure 5 reports the distribution of long-run changes in decadal averages of degree days above 18°C. Panel (a) reports the distribution 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. 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 CDD in deviation 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 60 degree days (see Table 1), while after removing division fixed effects, a standard deviation in the same variable corresponds to 43 degree days. We rely on this variation in our estimates of long-run effects of changes in average climate on manufacturing activity. Appendix Figure A.9 reports the geographical distribution of long-run changes in degree days in deviation from division-specific averages, showing that

[17] This implies that a day with average temperature of 20°C will correspond to 2 CDD and a day with average 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. The definition of CDD using deviations of average daily temperature from a certain threshold is also adopted by the U.S. Energy Information Administration (`https://www.eia.gov/energyexplained/units-and-calculators/degree-days.php`) and the National Oceanic and Atmospheric Service (`https://www.weather.gov/key/climate_heat_cool`).

[18] Heating Degree Days ($HDDs$) are defined in the same way for days with an average daily temperature below 18°C. Long run changes in $HDDs$ are included as a control in all specifications.

substantial variation exists across all regions.

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 account for 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 4, 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 and income per capita, and a negative correlation with the 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), and find no significant correlation.

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 Panel B of Table 4, 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 4, and also control for long-run changes in average precipitation and frequency of hurricanes and tornadoes, i.e. natural hazards that are not mechanically a function of temperature.

IV.B Results

IV.B.1 Number of Plants, Employment and Average Plant Size

We begin by examining how long-run changes in temperature affect long-run changes in the number of plants and total employment, separately for small and large plants, within a given CZ. The results are visualized in Figure 6 and reported in Table 5. The point estimates reported in columns (1) and (2) of Table 5 indicate that CZs that have become warmer over the last four decades experience a relative decline in the number of small plants. The magnitudes imply that CZs experiencing a standard deviation higher increase in temperature between the 1980s and 2010s– about 60 degree days above 18°C – witnessed a 4.5% larger decline in the number of small manufacturing plants. As before, we define as small the plants in the bottom 4 quintiles of the firm size distribution. This effect remains stable in magnitude and statistically significant at standard levels when we control for the set of initial CZ characteristics described in Section IV.A. The relative decline in the number of small plants does not translate into an increase in the number of large plants, as shown in columns (3) and (4). This indicates that the effect on small plants is not driven by a higher transition from small to large plants in areas that are getting warmer at a faster pace.

Next, we investigate the long-run effects of higher average temperatures on the number of workers employed by small and large plants. The results are visualized in the bottom panel of Figure 6 and reported in columns (5) to (8) of Table 5. We find negative and significant effects of long-run changes in average temperatures on employment in small plants. The estimated coefficient in column (6) indicates that CZs with a standard deviation higher increase in temperature between the 1980s and 2010s– about 60 degree days above 18°C – experienced a 7% larger decline in the number of workers employed by small manufacturing plants. This corresponds to around 320 manufacturing workers in the average commuting zone. The point estimates on the number of workers in large plants are positive although noisy. Their sign and magnitude suggest that while the number of large plants did not increase, such plants might have absorbed the labor force

released by smaller manufacturing establishments.

Table 6 reports the effects of long-run changes in temperature on total number of plants, total employment, and average plant size in a given CZ. As shown, areas that have become warmer over the last four decades experience a relative decline in the number of plants. The magnitude of the estimated coefficient in the specification with all controls implies that a standard deviation higher increase in temperature – about 60 degree days above 18°C per year – corresponds to a 4% 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 effect on the average plant size. Overall, these results indicate that CZs with faster warming temperatures experienced higher exit of small plants and no significant changes in total employment or in the number of large plants, which is consistent with a reallocation of workers from small to large plants.

We also investigate the long run effects of changes in average temperature on physical capital used by manufacturing plants. Table A.8 reports the results of estimating the same specification as Table 6 when the outcome variable is the capital-to-labor ratio in a given commuting zone. Capital is measured as book value of buildings, machinery and equipment, and labor is measured as number of workers. Column (1) shows that commuting zones with larger increases in average temperatures in the last four decades experienced a positive and significant increase in capital intensity of local manufacturing. This is possibly due to reallocation of economic activity towards larger plants, which tend to be more capital intensive. In columns (2) and (3) we separate capital into two main categories: buildings vs machinery and equipment. As shown, the results are mostly driven by a relative increase in the ratio of machinery and equipment vs labor in production.

IV.B.2 Concentration of Manufacturing Activity

Both the short- and the long-run effects analysis show that small plants are more vulnerable to temperature shocks and long run changes in climate conditions. Given these heterogeneous effects across the plant size distribution, we are interested in measuring

the impact of changes in temperature on industrial concentration. Following the previous literature, we focus on concentration within manufacturing sectors, and thus 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-5 largest plants and the Herfindahl-Hirschman Index (HHI) in a given CZ and sector. We compute the HHI as the sum of squared values of the employment shares of each plant in a given CZ-sector. 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 Table 7. 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 5 largest plants, and a 3.1 percent larger increase in the HHI.

One potential concern with the results in Table 7 is that they might be driven by relatively small CZ-sectors, and thus have negligible implications for concentration of manufacturing activity at the aggregate level. For more aggregate references, in Table A.9 we replicate the results in Table 7 weighting each observation by the number of employees in a given commuting zone and sector in the baseline period. As shown, when weighting observations by their size in terms of number of workers, we find larger and more precisely estimated effects. The magnitudes imply 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 1 percentage points larger increase in the share of employment concentrated in the top 5 largest plants, and a 8.1% 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

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 three potential mechanisms: energy prices, managerial skills, and access to finance.

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.[19] 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.

Higher prices per unit of energy translate into larger cost shocks for small than for large plants for a given increase in energy demand. 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

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

with dummies capturing terciles of average electricity prices (dollars per unit of energy) at the NAICS-3 industry and Census region level. As shown in Figure A.10, 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.[20]

The results in Panel A of Table 8 show that long-run changes in temperature have no effect on concentration in industry-regions facing the lowest cost per unit of energy (bottom tercile). The effect becomes positive, significant and monotonically increasing in size for industry-regions facing higher energy costs. In particular, for a one standard deviation in long-run temperatures, industry-regions in the top tercile of energy costs experience a 1.3 percentage points larger increase in the share of employment in the top 5 largest plants and a 6.1 percent larger increase in HHI relative to industry-regions in the first tercile. 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

[20]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.

number of employees (Figure A2 in Bloom et al. 2019).

Second, previous work also establish 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 productivity 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 energy management practices at the industry-level from the Manufacturing Energy Consumption Survey of 1998. We then sort industries into terciles of 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 B of Table 8. As shown, we find that higher participation rates in energy management lead to a lower impact of long-run changes in temperatures on industry concentration. In particular, the point estimates in column (2) indicate that the effect of long-run changes in temperature on concentration is 50% smaller in industries in the top tercile of adoption of energy management practices relative to those in the bottom tercile.

IV.C.3 Access to finance

Another potential mechanism linking size with better adaptation to climate change is that large plants might also have better access to external finance. This would allow them to use available credits 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 U.S. 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 C of Table 8. We find positive and significant effects of long-run changes in temperatures on local industry concentration in areas with the lowest local bank branch density. The effects are similar in the second tercile. Although the point estimates are only marginally significant, we find negative coefficients in areas with higher bank branch density, whose magnitudes are consistent with access to external finance favoring adaptation to long-run changes in temperatures. Still, 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.

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. The evidence indicates that differences in costs per unit of energy, managerial skill, and – to a more limited extent – access to finance play an important role. These 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 industrial production 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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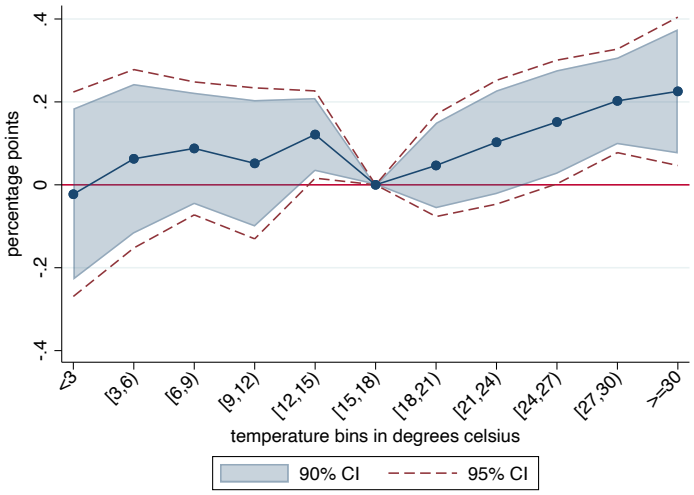
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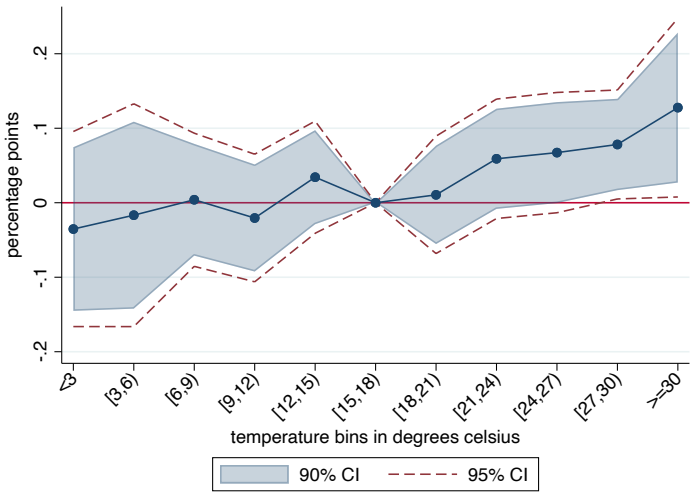
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FIGURE 1: SHORT-RUN EFFECTS OF TEMPERATURE ON ENERGY AND ELECTRICITY COSTS

Panel A: Energy Costs/Total Value of Shipments



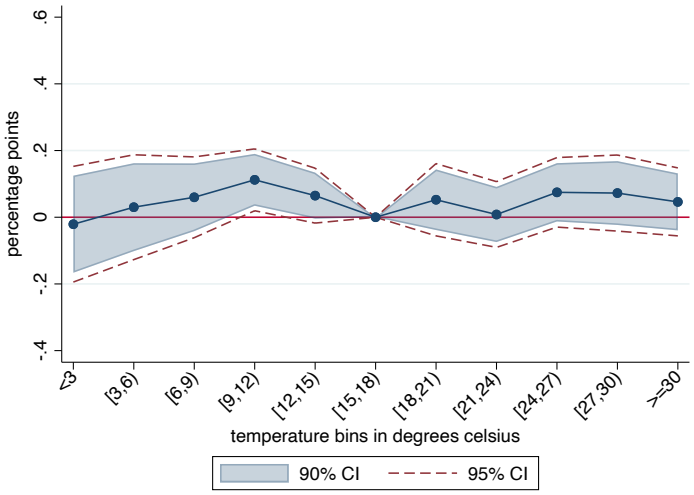
Panel B: Electricity Costs/Total Value of Shipments



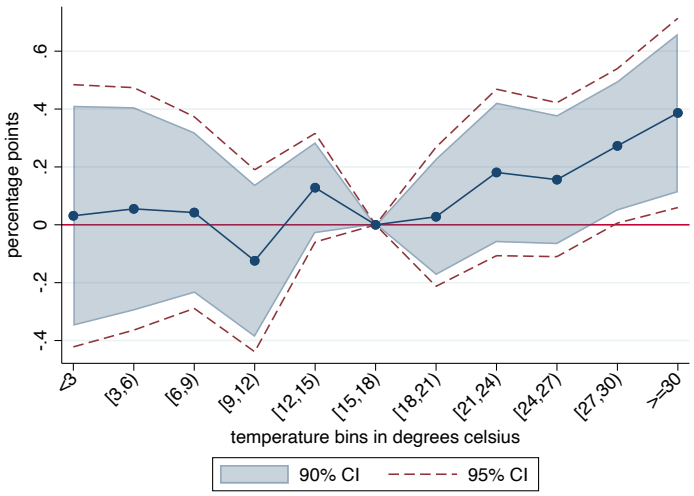
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments (Panel (a)) and electricity costs divided by total value of 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 2: SHORT-RUN EFFECTS OF TEMPERATURE ON ENERGY COSTS BY PLANT SIZE

Panel A: Large Plants



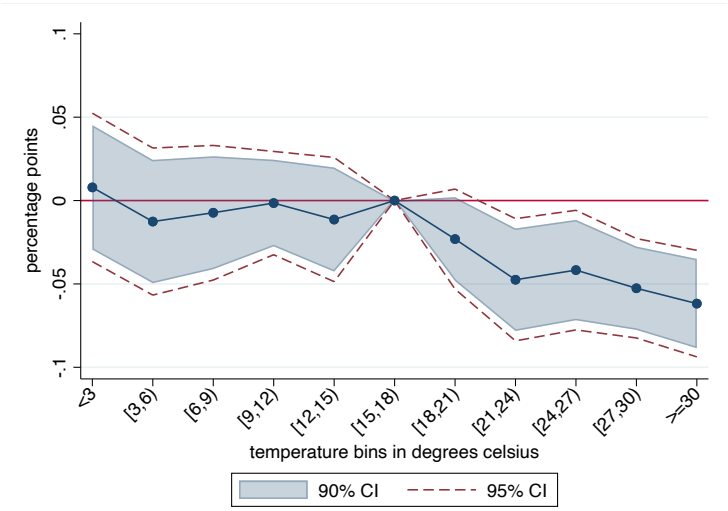
Panel B: Difference between Small and Large Plants



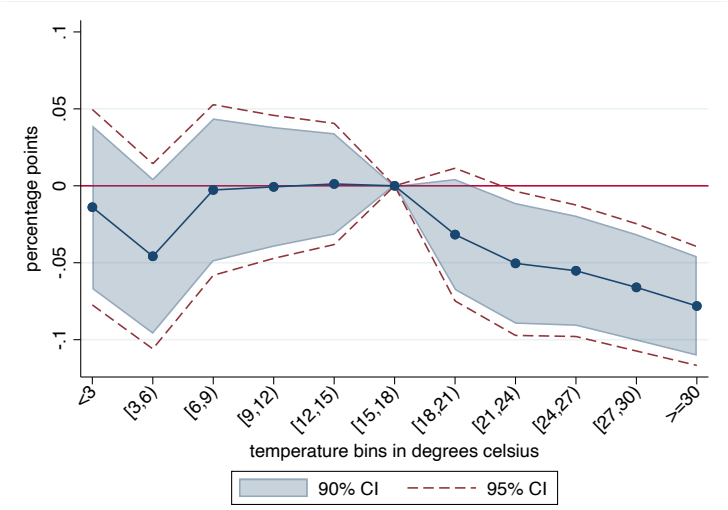
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments on large plants (Panel (a)) and on the difference between small and large plants (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. The cut-off for large and small plants is determined each industry-year using the number of employees at plant level. Large plants are those in the top quintile, and small plants are those in the bottom four quintiles. 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 3: SHORT-RUN EFFECTS OF TEMPERATURE ON PRODUCTIVITY

Panel A: Log(Total Factor Productivity)



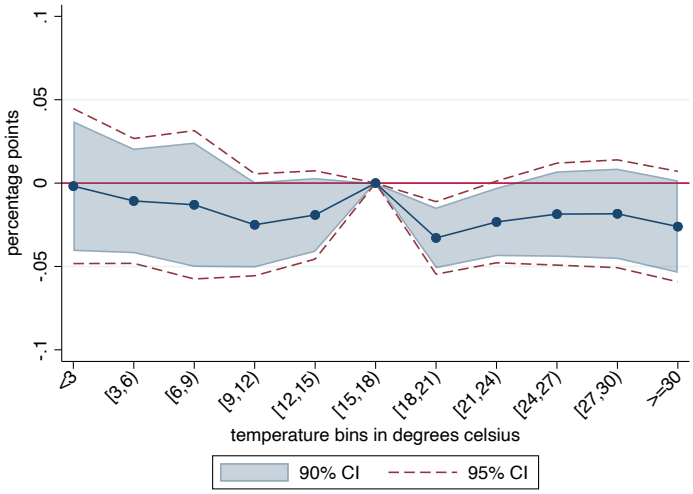
Panel B: Log(Value-Added / Total Hours Worked)



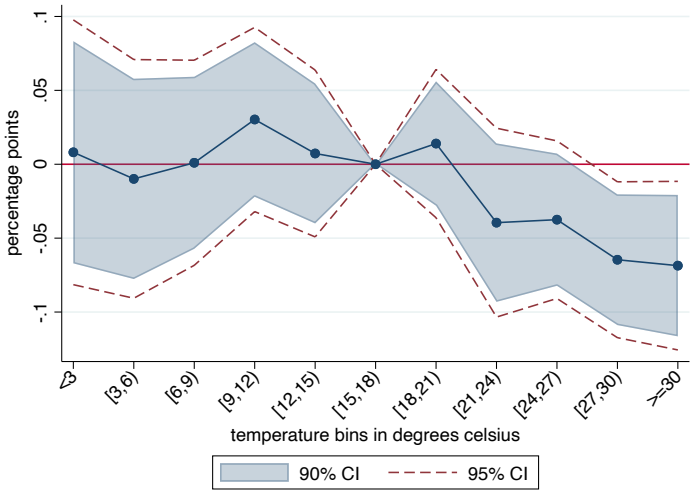
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP) (Panel (a)) and the natural logarithm of value-added divided by total hours worked (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 4: Short-run effects of temperature on productivity by plant size

Panel A: Large Plants



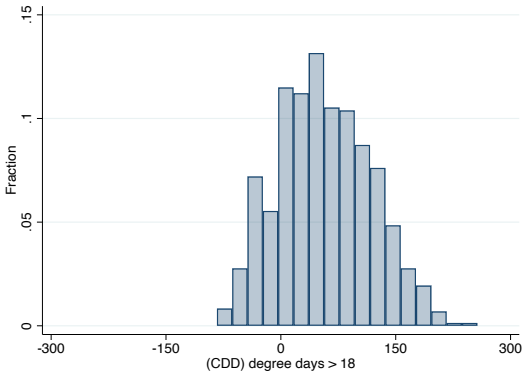
Panel B: Difference between Small and Large Plants



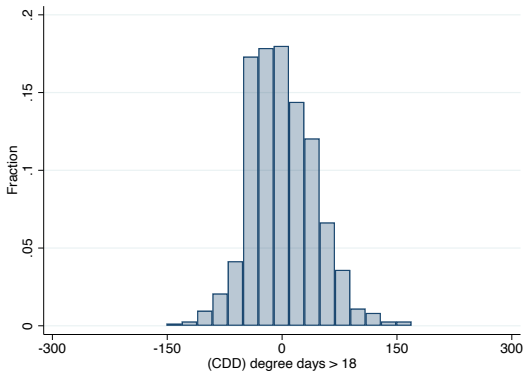
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP) on large firms (Panel (a)) and on the difference between small and large plants (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. The cut-off for large and small plants is determined each industry-year using the number of employees at plant level. Large plants are those in the top quintile, and small plants are those in the bottom four quintiles. 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: Distribution of long-run changes in cooling degree days (CDDs)

(a) Raw changes

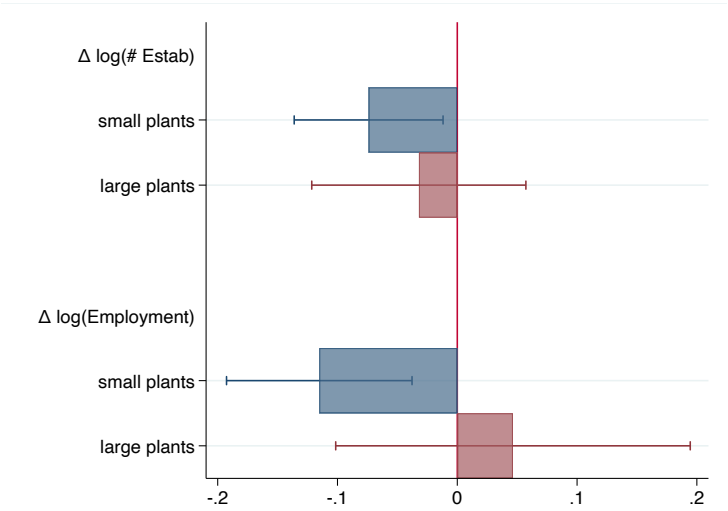


(b) Changes residualized on Census Division FE



Notes: The figure shows the distribution of changes in Cooling Degree Days (CDD) from the 1980s to the 2010s at the commuting zone level. A daily CDD is the difference in degrees between the average daily temperature and 18°C conditional on the average daily temperature being above 18°C, see Heutel et al. (2021) or Zivin and Kahn (2016). For each commuting zone, daily CDDs are summed by year; yearly CDDs are then averaged over the 1980s and 2010s, 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 6: Long-run effects of temperature on number of plants and employment



Notes: The figure illustrates the results of Table 5 by showing the point estimates and the 95% confidence intervals when using the commuting-zone-level long-run approach described in equation (2) to estimate the long-run effects of temperature on the number of plants and the number of employees for small vs large plants. The top panel shows results for the change in the natural logarithm of the average yearly number of plants between the 1980s and 2010s. The bottom panel shows results for the change in the natural logarithm of the average yearly number of employees reported by establishments. The coefficient of interest is the change in average Cooling Degree Days (Δ Degree-Days > 18°C) between the 1980s and the 2010s at the commuting zone level, in unit of 100 degree days. CZ-level controls include the change in Heating Degree Days between the 1980s and the 2010s, the change in average precipitation between the 1980s and the 2010s, percentage of the 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 1980s and 2010s. Census Division fixed effects are included. Standard errors are clustered at the state level.

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
$3°C \leq T < 6°C$	1922000	17.92	12.55
$6°C \leq T < 9°C$	1922000	20.16	12.28
$9°C \leq T < 12°C$	1922000	22.54	11.83
$12°C \leq T < 15°C$	1922000	26.17	10.87
$15°C \leq T < 18°C$	1922000	29.78	10.28
$18°C \leq T < 21°C$	1922000	33.21	11.66
$21°C \leq T < 24°C$	1922000	37.01	12.83
$24°C \leq T < 27°C$	1922000	42.84	13.01
$27°C \leq T < 30°C$	1922000	44.59	15.11
$T \geq 30°C$	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	57.08	60.4
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	63.02	57.48
Δ Fraction of Emp. in Top 5 Largest Estab.	11000	-0.0003	0.092
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). The unit of measurement for Δ Degree-Days $> 18°C$ is 100 degree days. Variable definitions are in Appendix Table A.1.

Table 2: Short-run effects of temperature on energy and electricity 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 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 3: Short-run effects of temperature on productivity

	Log(TFP)		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 the natural logarithm of total factor productivity (Columns 1-2) and the natural logarithm of value added divided by total hours worked (Columns 3-4). The analysis is at the plant-year level and the sample period comprises 1977-2018. 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 4: 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	-0.026*	0.027
	(0.014)	
log(pop.)	0.285	0.152
	(0.255)	
log(per cap. income)	-0.042	0.025
	(0.029)	
ΔIPW_{uit}	-0.184	0.018
	(0.580)	
Panel B: Long-run changes in the occurrences of natural hazards		
avg. precipitation	-0.148***	0.112
	(0.037)	
flood	-1.751	0.012
	(2.683)	
drought	9.718	0.015
	(7.633)	
heatwave	2.522	0.009
	(3.271)	
hurricane	1.291	0.011
	(2.018)	
tornado	-0.031	0.026
	(2.131)	
Observations	722	

Notes: The table provides the results of balance tests for commuting zone initial characteristics. Panel A reports coefficients from univariate regressions of commuting zone characteristics on changes in Cooling Degree Days (CDDs). ΔIPW captures exposure to China shock between 1991 and 2007, as defined in Autor et al. (2013). The other characteristics are from the 1980 Population Census. Panel B reports coefficients from univariate regressions of changes in the frequency of natural disasters between the 1980s and 2010s on changes in CDDs. The independent variables in both panels are changes in the number of CDDs (Δ Degree-Ddays > 18°C) from the 1980s to the 2010s, in unit of 100 degree days. All regressions also include long-run changes in Heating Degree Days. Standard errors are reported in parentheses and clustered at the state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

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

Dep. Var.	Δ Log(# Establishments)				Δ Log(Employment)			
	Small		Large		Small		Large	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Degree-Days > 18°C	-0.0958**	-0.0740**	0.0005	-0.0321	-0.1366***	-0.1152***	0.0687	0.0465
	(0.0380)	(0.0317)	(0.0510)	(0.0456)	(0.0400)	(0.0395)	(0.0745)	(0.0755)
Observations	700	700	650	650	700	700	650	650
R-squared	0.116	0.177	0.180	0.206	0.120	0.153	0.185	0.196
Census Division FE	yes	yes	yes	yes	yes	yes	yes	yes
Commuting-zone controls		yes		yes		yes		yes

Notes: The table shows the main coefficients when estimating the commuting-zone-level long-run specification described in equation (2) to examine the long-run effects of temperature on number of establishments and number of employees for small and large plants. Small plants are defined as those in the bottom four quintiles by number of employees in the 1980s. Large plants are those in the top quintile. The unit of measurement for Δ Degree-Days > 18°C is 100 degree days. Changes in Heating Degree Days and changes in average precipitation between the 1980s and the 2010s are included as controls throughout. Additional CZ-level controls include 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 1980s and the 2010s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 6: Long-run effects of temperature on number of plants, employment, and average plant size

Dep. Var.	Δ Log(# Estab.)		Δ Log(Emp.)		Δ Log(Avg. Size of Estab.)	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Degree-Days > 18°C	-0.0811*	-0.0654**	0.0362	0.029	0.1208**	0.0976*
	(0.0410)	(0.0321)	(0.0545)	(0.0522)	(0.0554)	(0.0552)
Obs	700	700	700	700	700	700
R-squared	0.152	0.214	0.19	0.216	0.146	0.168
Census Division FE	yes	yes	yes	yes	yes	yes
Commuting-zone controls		yes		yes		yes

Notes: The table reports the results obtained when estimating the commuting-zone-level long-run specification described in equation (2). In column (1)-(2), the outcome variable is the change in the natural logarithm of the average yearly number of establishments between the 1980s and the 2010s. In column (3)-(4), the outcome variable is the change in the natural logarithm of the average yearly number of employees reported by establishments between the 1980s and the 2010s. In column (5)-(6), the outcome variable is the change in the natural logarithm of the average number of employees per establishment between the 1980s and the 2010s. The unit of measurement for Δ Degree-Days > 18°C is 100 degree days. Changes in Heating Degree Days and changes in average precipitation between the 1980s and the 2010s are included as controls throughout. Additional CZ-level controls include 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 1980s and the 2010s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 7: Long-run effects of temperature on industrial concentration

Dep. Var.	Δ Frac. of Emp. in Top 5 Largest Estab.		Δ Log(HHI Emp.)	
	(1)	(2)	(3)	(4)
Δ Degree-Days > 18°C	0.0087**	0.0077**	0.0573***	0.0521***
	(0.0036)	(0.0034)	(0.0208)	(0.0184)
Obs	11000	11000	11000	11000
R-squared	0.147	0.151	0.139	0.143
Census Division FE	yes	yes	yes	yes
NAICS-3 FE	yes	yes	yes	yes
Commuting-zone controls		yes		yes

Notes: The table reports the results obtained by estimating the commuting-zone-NAICS-3-level long-run specification described in equation (2). In columns (1)-(2), the outcome variable is the change in the fraction of employees working in the 5 largest plants within each CZ-sector between the 1980s and the 2010s. In columns (3)-(4), the outcome variable is the change in the natural logarithm of the average yearly Herfindahl-Hirschman Index between the 1980s and the 2010s, constructed on the basis of the number of employees reported by establishments. The unit of measurement for Δ Degree-Days > 18°C is 100 degree days. Changes in Heating Degree Days and changes in average precipitation between the 1980s and the 2010s are included as controls throughout. Additional CZ-level controls include 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 1980s and the 2010s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

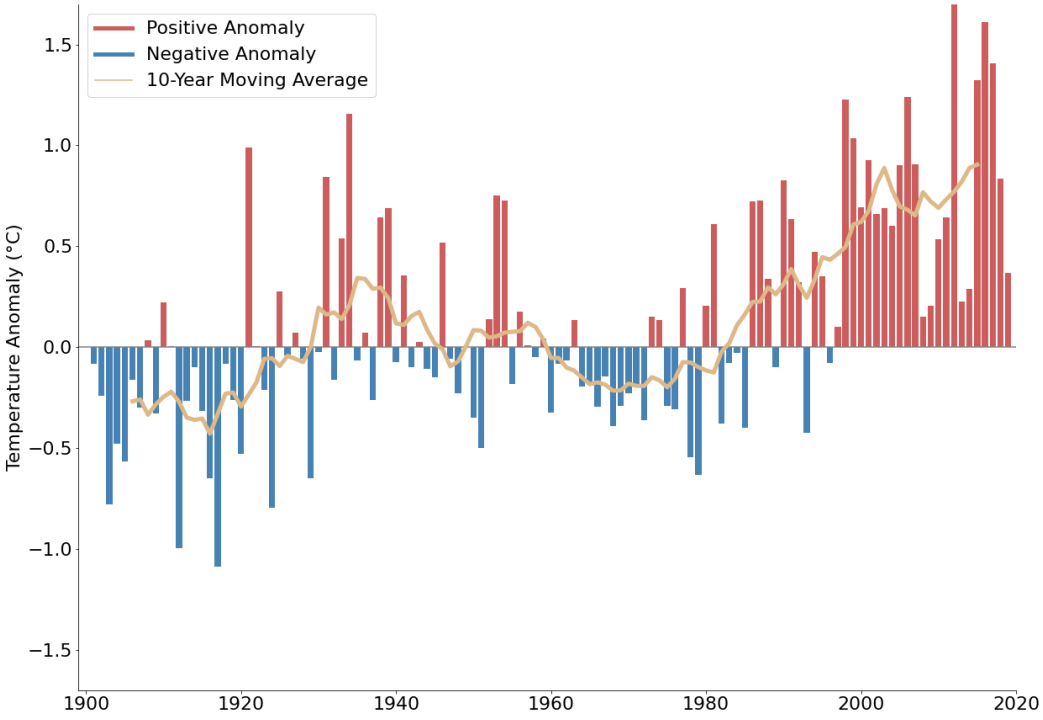
Table 8: Heterogeneous long-run effects of temperature on industrial concentration

Dep. Var.	Δ Frac. of Emp. in Top 5 Largest Estab. (1)	Δ Log(HHI Emp.) (2)
Panel A: Interacted with tercile indicators of electricity prices		
Δ Degree-Days > 18°C	-0.0041	0.0036
	(0.0036)	(0.0186)
Δ Degree-Days > 18°C × 2nd tercile	0.0158**	0.0488*
	(0.0063)	(0.0243)
Δ Degree-Days > 18°C × 3rd tercile (Highest)	0.0220***	0.1013**
	(0.0074)	(0.0388)
Panel B: Interacted with tercile indicators of energy management participation		
Δ Degree-Days > 18°C	0.0135***	0.0907***
	(0.0048)	(0.0294)
Δ Degree-Days > 18°C × 2nd tercile	-0.0087**	-0.0646**
	(0.0038)	(0.0245)
Δ Degree-Days > 18°C × 3rd tercile (Highest)	-0.0096*	-0.0535*
	(0.0048)	(0.0304)
Panel C: Interacted with tercile indicators of # of bank branches per 1000 people		
Δ Degree-Days > 18°C	0.0094*	0.0611**
	(0.0050)	(0.0236)
Δ Degree-Days > 18°C × 2nd tercile	-0.0019	-0.0095
	(0.0059)	(0.0333)
Δ Degree-Days > 18°C × 3rd tercile (Highest)	-0.0098*	-0.0449
	(0.0057)	(0.0303)
Observations	11000	11000
Census Division FE	yes	yes
NAICS-3 FE	yes	yes
Commuting-zone comtrols	yes	yes

Notes: The table shows the results obtained when estimating the commuting-zone-industry-level long-run specification described in equation (2). In column (1), the outcome variable is the change in the natural logarithm of the fraction of employment in the top 5 largest establishment between the 1980s and the 2010s. In column (2), the outcome variable is the change in the natural logarithm of the average yearly Herfindahl-Hirschman Index between the 1980s and the 2010s, constructed on the basis of the number of employees reported by establishments. In Panel A, the interaction terms are indicators for the second and third terciles of electricity prices in 1998, categorized by NAICS-3 industry and census regions. In Panel B, the interaction terms are indicators for the second and third terciles of energy management participation rates in 1998, categorized by NAICS-3 industry. In Panel C, the interaction terms are indicators for the second and third terciles of the number of branch per 1000 population in 1994. The unit of measurement for Δ Degree-Days > 18°C is 100 degree days. Census Division fixed effects and NAICS-3 fixed effects are included. Changes in Heating Degree Days interacted with the tercile indicators and changes in average precipitation between the 1980s and the 2010s are included as controls. Additional CZ-level controls are the same as in Table 7. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Internet Appendix

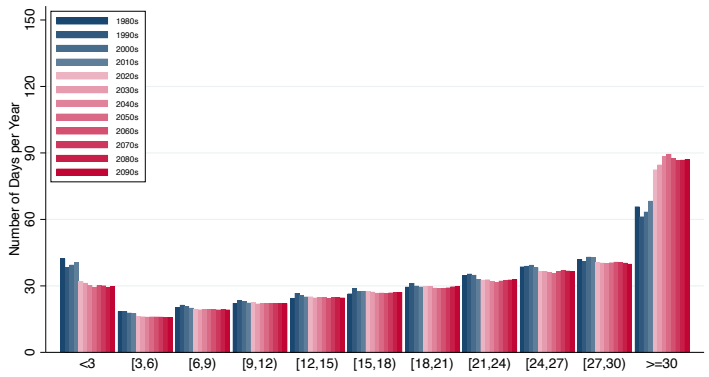
Figure A.1: Temperature trend in the U.S.



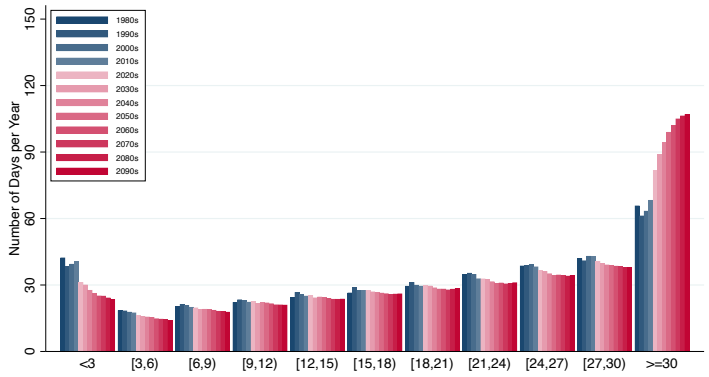
Notes: The figure shows annual and decadal temperature dynamics over the 1901 to 2019 period on the basis of temperature data obtained from the National Oceanic and Atmospheric Administration (NOAA). The underlying data covers 48 contiguous states. Annual anomalies (the bars) are defined as the difference 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 A.2: Historical and predicted distribution of maximum temperature days

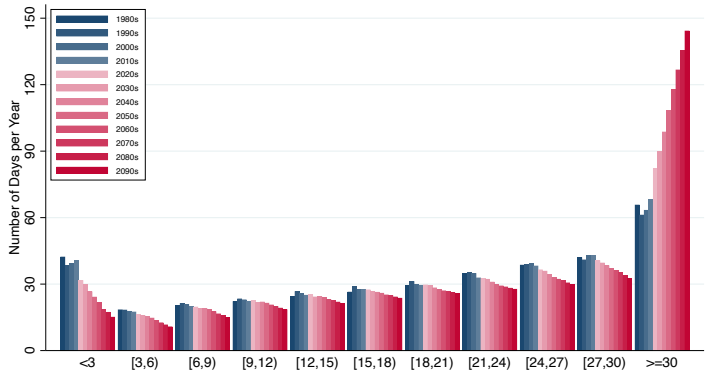
Panel A: Stringent Scenario (RCP 2.6)



Panel B: Intermediate Scenario (RCP 4.5)

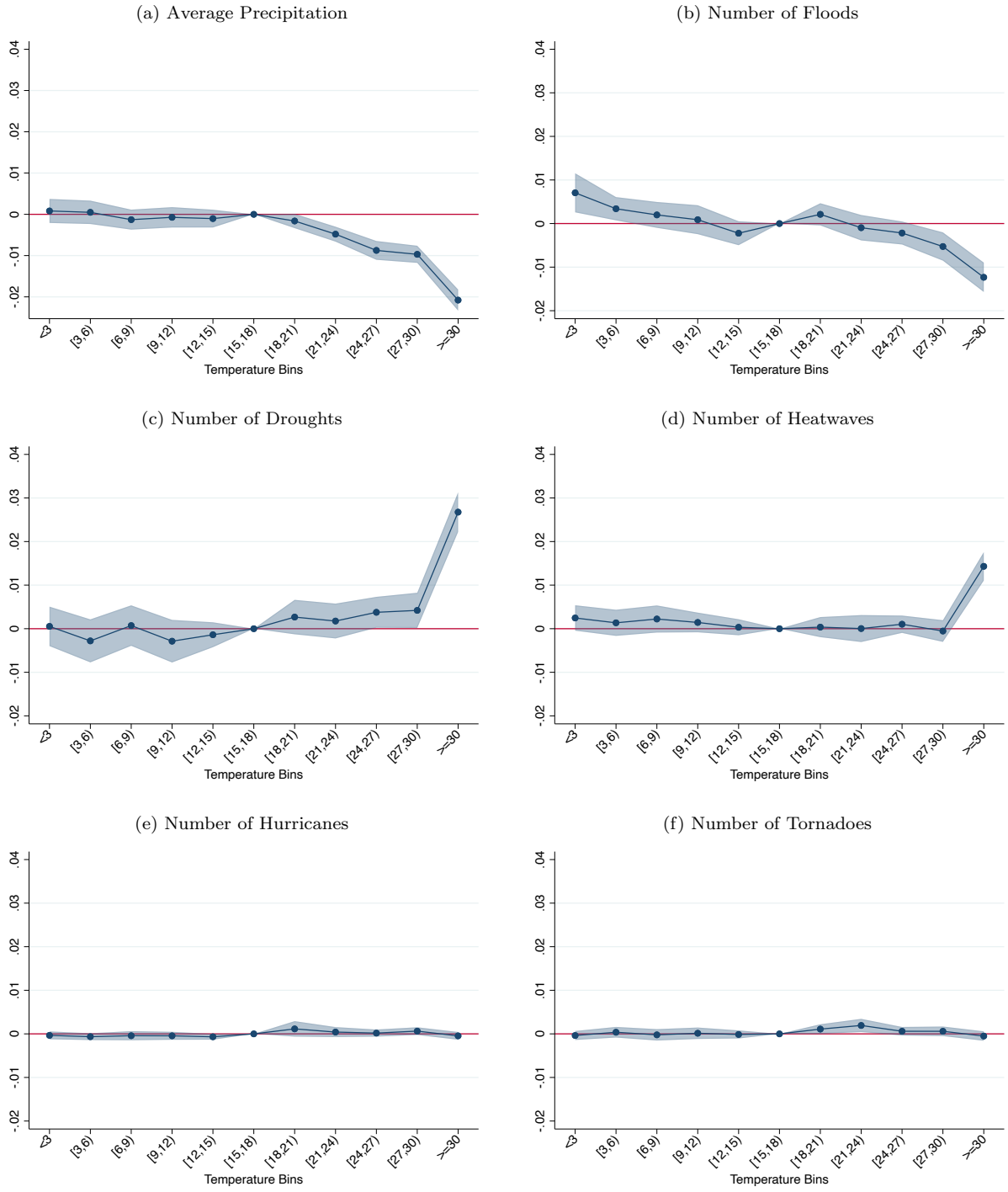


Panel C: High Greenhouse Gas Emission Scenario (RCP 8.5)



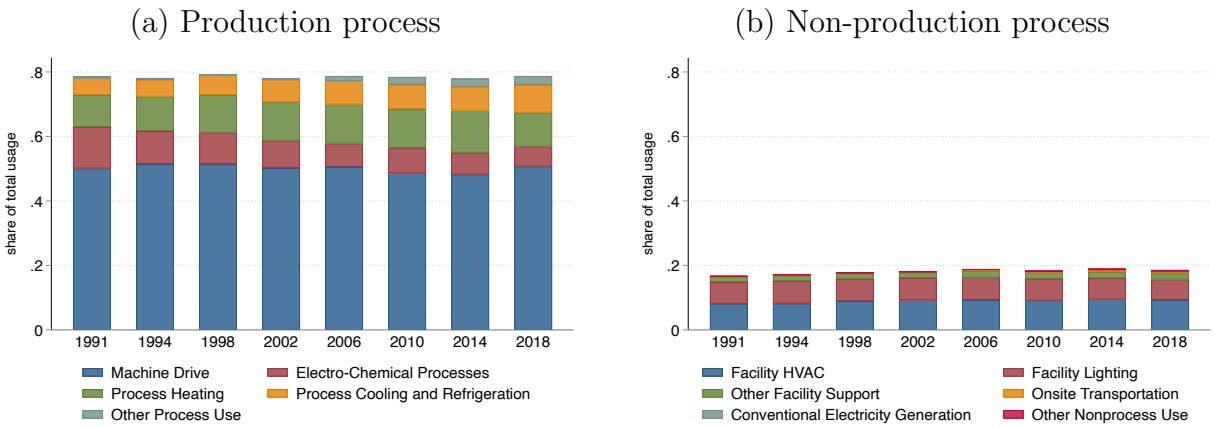
Notes: The figure shows decadal U.S. long-run temperature projections on the basis of big data generated by Hsiang et al. (2017) for the 1980s to 2090s. The underlying data are based on 44 climate models. Shown are projections under three different Representative Concentration Pathways (RCPs) used to 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.3: Short-run effects of 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).

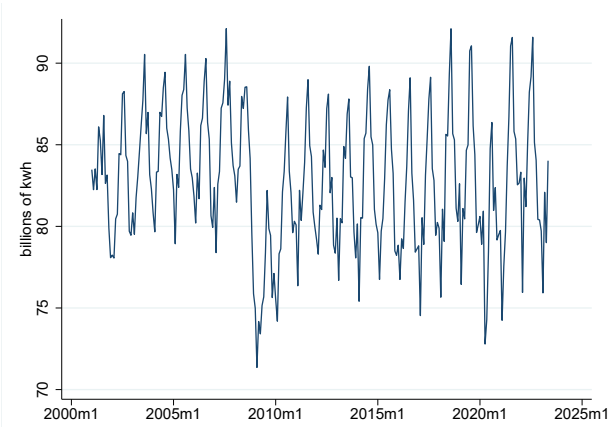
Figure A.4: Electricity Usage by U.S. Manufacturing Plants



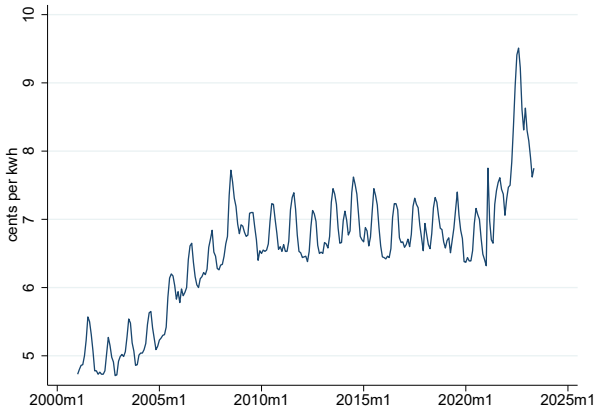
Notes: The figure shows average electricity usage by U.S. Manufacturing Plants in production (Panel (a)) and non-production (Panel (b)) processes. Underlying data are from the Manufacturing Energy Consumption Survey.

FIGURE A.5: SEASONALITY IN INDUSTRIAL ELECTRICITY DEMAND AND PRICES

(a) Electricity sales, industrial sector



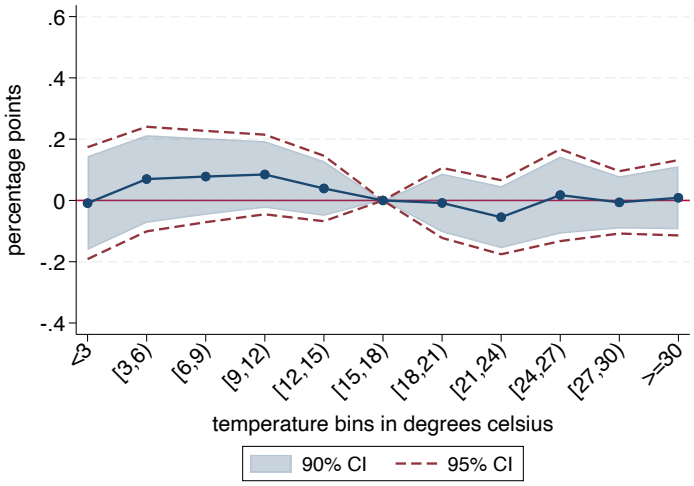
(b) Electricity prices, industrial sector



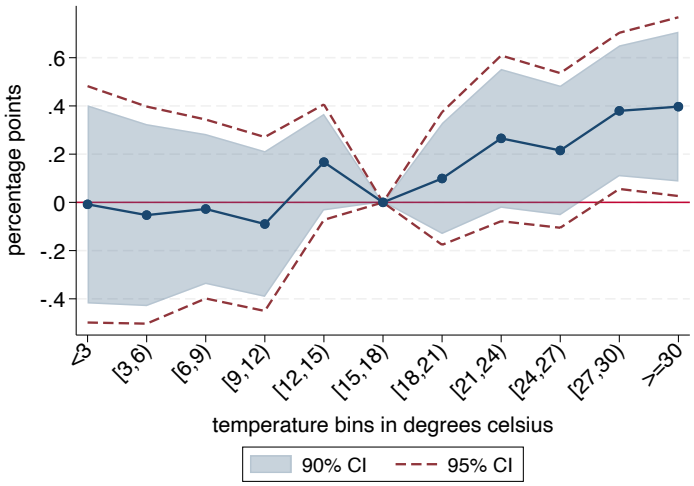
Notes: The figure shows average monthly electricity sales (Panel (a)) and average monthly electricity prices (Panel (b)) for the industrial sector. Underlying data are obtained from the Electric Power Monthly dataset available at `https://www.eia.gov/electricity/data.php` through the U.S. Energy Information Administration.

FIGURE A.6: SHORT-RUN EFFECTS OF TEMPERATURE ON ENERGY COSTS BY PLANT SIZE: ROBUSTNESS TO USING QUARTILES

Panel A: Large Plants



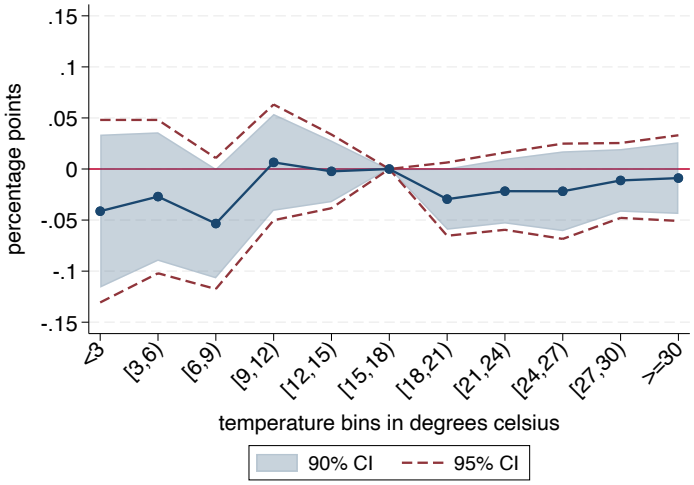
Panel B: Difference between Small and Large Plants



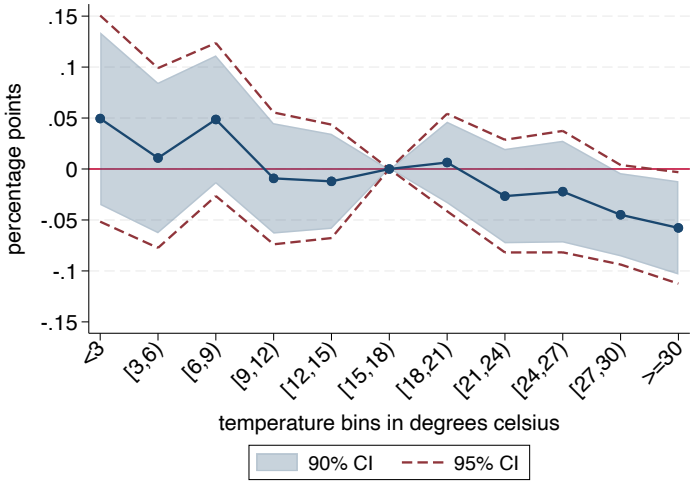
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments on large plants (Panel (a)) and on the difference between small and large plants (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. The cut-off for large and small plants is determined each industry-year using the number of employees at plant level. Large plants are those in the top quartile, and small plants are those in the bottom three quartiles. 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 A.7: Short-run effects of temperature: Difference between private-owned and public-owned plants

Panel A: Plants of Public Firms



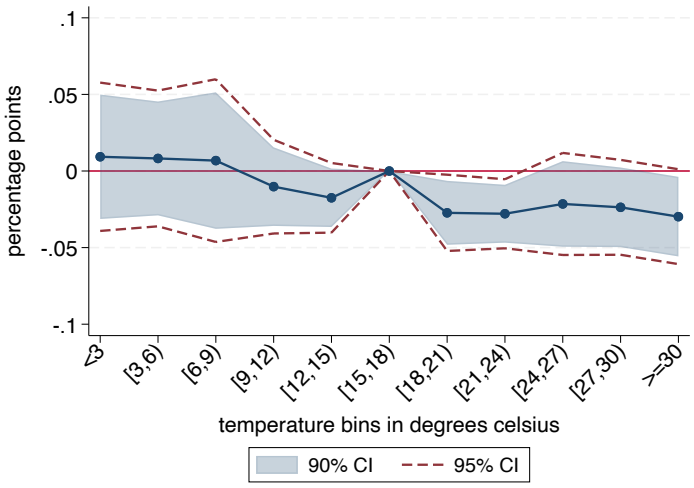
Panel B: Difference Between Plants of Private vs Public Firms



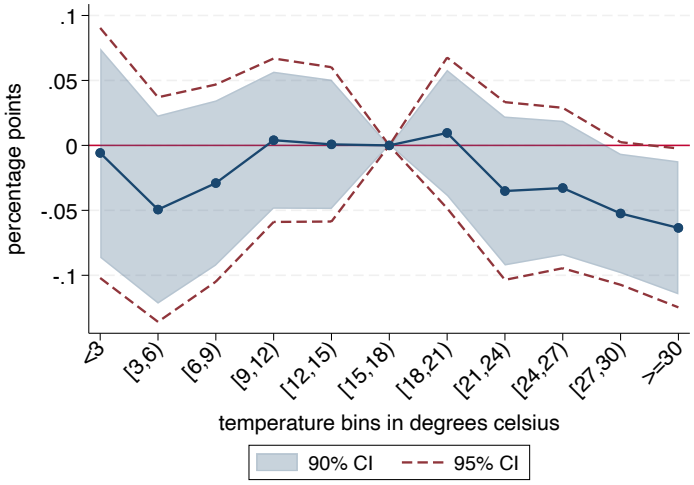
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP) on plants owned by publicly listed firms (Panel (a)) and on the difference between plants owned by private firms vs publicly listed 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. 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 A.8: SHORT-RUN EFFECTS OF TEMPERATURE ON PRODUCTIVITY BY PLANT SIZE: ROBUSTNESS TO USING QUARTILES

Panel A: Large Plants

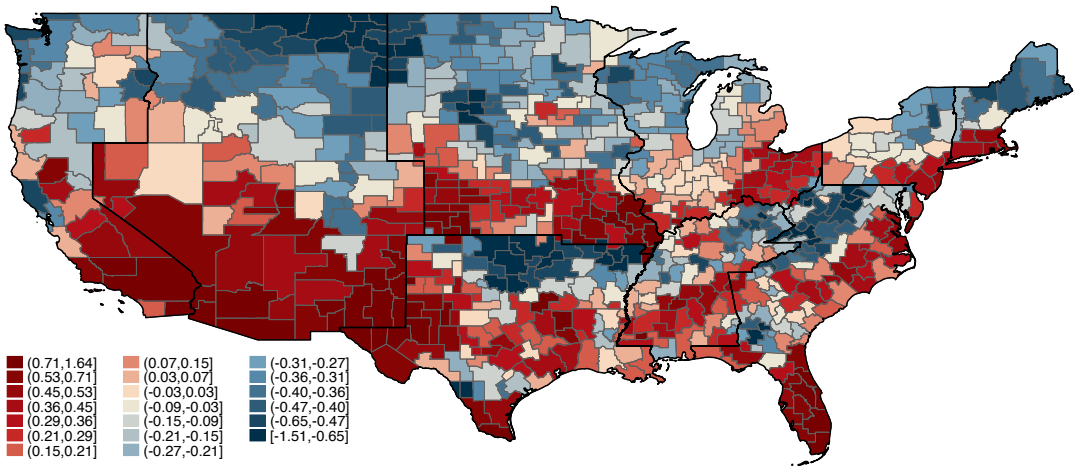


Panel B: Difference between Small and Large Plants



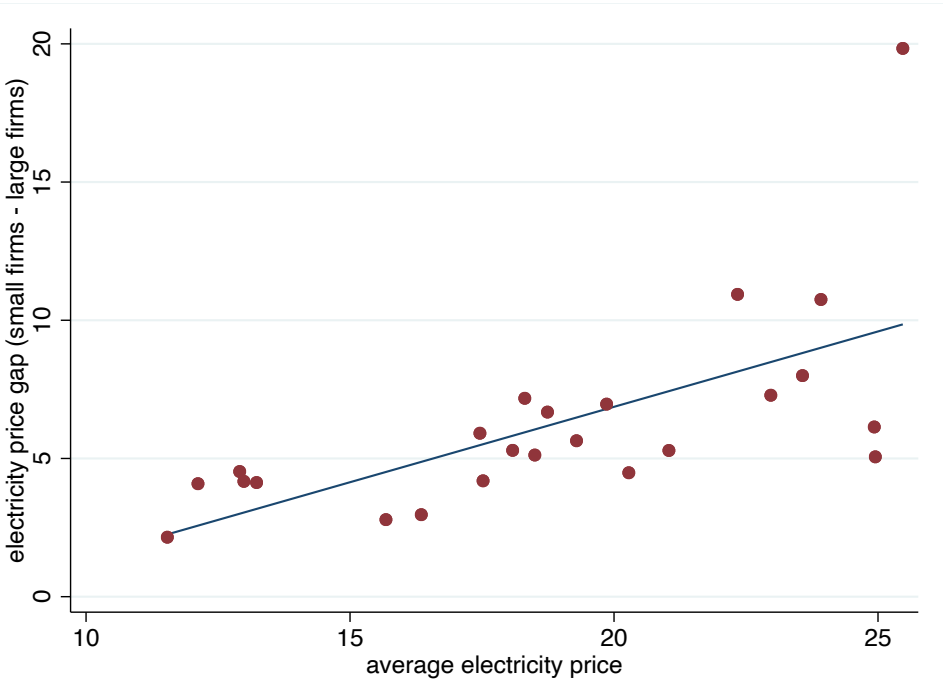
Notes: The figure shows the point estimates and the 90/95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effects of temperature on the natural logarithm of total factor productivity (TFP) on large firms (Panel (a)) and on the difference between small and large plants (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. The cut-off for large and small plants is determined each industry-year using the number of employees at plant level. Large plants are those in the top quartile, and small plants are those in the bottom three quartiles. 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 A.9: Geographic distribution of long-run changes in cooling degree days (CDDs)



Notes: The figure shows changes in Cooling Degree Days (CDDs) between the 1980s and the 2010s by commuting zone relative to average Census division changes. Census Division borders are shown in solid black lines. A Cooling Degree Day (CDD) is the difference in degrees between the average daily temperature and 18°C conditional on the average daily temperature being above 18°C, see Heutel et al. (2021) or Zivin and Kahn (2016). For each commuting zone, daily CDDs are summed by year, yearly CDDs are then averaged over the 1980s and 2010s, respectively, from which the long-run difference is calculated. The unit of measure is 100 degree days. 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 relative to division-level changes.

Figure A.10: Correlation between average electricity price and the price gap between small and large plants



Notes: The figure visualizes the 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. Underlying data are obtained from 1998, 2002, 2006, 2010, 2014, and 2018 Manufacturing Energy Consumption Survey.

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.	US Census
Electricity Costs / TVS (%)	The ratio of electricity costs to total value of shipments.	US Census
Log(TFP)	Log of total factor productivity.	US Census
Log(Value-Added/Total Hours Worked)	Log of the ratio of value-added to workers' total working hours.	US Census
Log(Total Hours Worked)	Log of workers' total working hours.	US Census
Log(TVS)	Log of total value of shipments.	US Census
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.	US Census US Census
Panel C: LBD - Long-run difference between the 1980s and the 2010s		
Δ Degree-Days $>$ 18 °C	Long-difference in average degree days above 18 °C (in unit of 100 degree days) from 1980s to 2010s.	US Census
Δ Log(# Establishments)	Long-difference in log of average total establishment from 1980s to 2010s.	US Census
Δ Log(Employment)	Long-difference in log of average total employment from 1980s to 2010s.	US Census
Δ Log(Avg. Size of Establishments)	Long-difference in log of average employment size from 1980s to 2010s.	US Census
Δ Frac. of Emp. in Top 5 Largest Estab.	Long-difference in the average fraction of employment in the top 5 establishments (by number of employees) from 1980s to 2010s.	US Census
Δ Log(HHI Emp.)	Long-difference in the average HHI of employment from 1980s to 2010s.	US Census
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: 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 3 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 effects 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 natural logarithm of 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. 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 in Column (1). 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: 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 columns (1) and (2) of Tables 2 and 3, restricting the sample to highly tradable manufacturing sectors. Highly 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: Robustness to excluding sectors dependent on Agriculture

	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 columns (1) and (2) of Tables 2 and 3, 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: Robustness to Alternative temperature definition

	Energy Costs/TVS (1)	Log(TFP) (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
Extreme weather controls	yes	yes
State-year FE	yes	yes

Notes: In this table Panel A, we replicate the results presented in column (2) of Tables 2 and 3, using temperature bins constructed on the basis of average (instead of maximum) daily temperatures. The number of days with average daily temperature in a temperature bin is divided by 100 for readability and the temperature bin [9°C,12°C) is used as the reference bin and therefore omitted. In Panel B, we employ a continuous specification using Cooling Degree Days (CDD) and Heating Degree Days (HDD). CDD (HDD) is defined as the number of degrees by which the average daily temperature exceeds (falls below) 18°C, conditional on being above (below) this threshold. 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.7: SHORT-RUN EFFECTS OF TEMPERATURE: NORTH AND SOUTH

	North		South	
Dep.Var.	Energy Costs/TVS	Log(TFP)	Energy Costs/TVS	Log(TFP)
	(1)	(2)	(3)	(4)
T < 3°C	-0.0556	0.0282		
	(0.1305)	(0.0229)		
3°C ≤ T < 6°C	0.0063	0.0099		
	(0.1233)	(0.0246)		
6°C ≤ T < 9°C	0.0368	0.0188		
	(0.0883)	(0.0237)		
9°C ≤ T < 12°C	-0.0685	0.016	0.2950**	-0.1101***
	(0.1044)	(0.0191)	(0.1195)	(0.0262)
12°C ≤ T < 15°C	0.0883	0.0068	0.2251**	-0.0756*
	(0.0670)	(0.0221)	(0.0986)	(0.0396)
18°C ≤ T < 21°C	0.0827	-0.0131	0.1268	-0.0745**
	(0.0579)	(0.0178)	(0.1953)	(0.0338)
21°C ≤ T < 24°C	0.1143	-0.0533**	0.0692	-0.0671*
	(0.0781)	(0.0230)	(0.2044)	(0.0360)
24°C ≤ T < 27°C	0.1612**	-0.0398	0.135	-0.0696***
	(0.0733)	(0.0239)	(0.2380)	(0.0205)
27°C ≤ T < 30°C	0.2032***	-0.0505***	0.2611	-0.0612**
	(0.0660)	(0.0179)	(0.2010)	(0.0247)
T ≥ 30°C	0.2119*	-0.0572***	0.2473	-0.0629*
	(0.1250)	(0.0208)	(0.2357)	(0.0346)
Observations	1442000	1442000	480000	480000
R-squared	0.793	0.787	0.813	0.777
Establishment FE	yes	yes	yes	yes
NAICS3-Year FE	yes	yes	yes	yes
State-year FE	yes	yes	yes	yes

Notes: In this table, we replicate the results presented in Tables 2 and 3, splitting the sample into Northern and Southern U.S. regions. Southern regions are those in the top 25% by average annual Cooling Degree Days, and Northern regions are all remaining regions. For the subsample of Southern regions, days with maximum temperature below 9°C are grouped into the [9°C-12°C) bin due to extremely limited number of observations in lower temperature ranges. 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.8: Long-run effects of temperature on capital

Dep.Var.	Δ Log($\frac{\text{Total Capital}}{\text{Employment}}$) (1)	Δ Log($\frac{\text{Structure Capital}}{\text{Employment}}$) (2)	Δ Log($\frac{\text{Equipment Capital}}{\text{Employment}}$) (3)
Δ Degree-Days $>$ 18°C	0.1422**	0.0574	0.1814***
	(0.0599)	(0.0743)	(0.0586)
Observations	650	650	650
R-squared	0.101	0.087	0.118
Census Division FE	yes	yes	yes
Commuting-zone controls	yes	yes	yes

Notes: The table reports results obtained when estimating the commuting-zone-level long-run specification described in equation (2). Outcome variables include the change in the natural logarithm of the total capital to employment ratio from between the 1980s and the 2010s (column (1)) and respective changes in structure capital to employment ratio (column (2)) and equipment capital to employment ratio (column (3)). The unit of measurement for Δ Degree-Days $>$ 18°C is 100 degree days. Changes in Heating Degree Days and changes in average precipitation between the 1980s and the 2010s are included as controls throughout. Additional CZ-level controls include 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 1980s and the 2010s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.9: Long-run effects of temperature on industrial concentration: weighted regression

Dep. Var.	Δ Frac. of Emp. in Top 5 Largest Estab.		Δ Log(HHI_Emp.)	
	(1)	(2)	(3)	(4)
Δ Degree-Days > 18°C	0.0200***	0.0142***	0.1654***	0.1349***
	(0.0041)	(0.0044)	(0.0392)	(0.0374)
Observations	11000	11000	11000	11000
R-squared	0.39	0.394	0.396	0.398
Census Division FE	yes	yes	yes	yes
NAICS-3 FE	yes	yes	yes	yes
Commuting-zone controls		yes		yes

Notes: In this table, we replicate the results presented in Table 7 but weigh observations by the number of employees of each CZ-NAICS3 observation in the 1980s. In columns (1)-(2), the outcome variable is the change in the fraction of employees working in the 5 largest plants within each CZ-sector between the 1980s and the 2010s. In columns (3)-(4), the left-hand side variable is the change in the natural logarithm of the average yearly Herfindahl-Hirschman Index between the 1980s and the 2010s, constructed on the basis of the number of employees reported by establishments. The unit of measurement for Δ Degree-Days > 18°C is 100 degree days. Changes in Heating Degree Days and changes in average precipitation between the 1980s and the 2010s are included as controls throughout. Additional CZ-level controls include 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 1980s and the 2010s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.