Temperature, Adaptation, and Local Industry Concentration*

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Abstract

We use plant-level data from the U.S. Census of Manufacturers to study the short- and long-run effects of temperature on manufacturing activity. We find that high-temperature shocks significantly increase energy costs and lower productivity for small plants, while large plants are mostly unaffected. Commuting zones with higher increases in average temperatures between the 1980s and the 2010s experience a decline in the number of small plants, reallocation of labor from small to large plants, and higher local labor market concentration. Differences in costs per unit of energy, managerial skills, and access to finance contribute to explaining our results.

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

JEL Classification: Q54, O14, G3, L11

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I Introduction

Average global temperatures increased substantially over the 20th century and will continue to rise (IPCC, 2021). In the continental United States, the pace of warming started accelerating in the 1980s, with a county-level median increase in temperatures of 0.6°C from the 1980s to the 2010s and nine in ten counties experiencing higher average temperatures over that period. Even under optimistic climate mitigation scenarios, the average number of days above 26°C is expected to double from 20 days in the 2010s to 40 days by the end of the 21st century. Under worst-case scenarios, this number is expected to quintuple.[1] These facts and projections have put the effects of a warming climate on socioeconomic outcomes at the center of political and academic debates.

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

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

We combine the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM) to measure plants' energy costs, productivity, and size, and use the Longitudinal Business Database (LBD), an administrative register that tracks all business establishments in the US, to identify plant entry and exit in different geographic locations.

In order to estimate the effect of temperature on manufacturing plants, we employ

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

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

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

Two key findings emerge from our estimates of the short-run effects of temperature shocks on manufacturing outcomes. First, the input costs associated with temperature management (expenditures in electricity and fuel) and productivity react to contemporaneous temperature shocks. In particular, warmer than average temperatures increase energy costs and decrease plant productivity. Second, these effects are concentrated in small manufacturing plants, while large establishments are mostly unaffected.

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

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

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

We find that, over the last four decades, areas where the climate got warmer at a faster pace experienced larger declines in the number of small plants but no differential change in the number of large plants. We also find that large plants absorbed at least part of the labor force released by smaller manufacturing establishments. This is consistent with reallocation of employment from small to large plants in CZs that experienced a higher increase in temperature over the last four decades.

Next, we investigate the impact of higher average temperatures on different measures of concentration at the CZ-sector level. We find that industries in CZs that in the 2010s had a standard deviation higher increase in temperature – about 60 cooling degree days (CDDs) per year above 18°C – relative to the 1980s, experienced 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).[2] Consistent with these results, we also document a large and significant increase in the average size of manufacturing plants in CZs that are getting warmer at a faster pace (6% larger average plant size for a one standard deviation increase in CDDs).

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

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

[2] A daily 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, see Heutel et al. (2021) or Zivin and Kahn (2016). Yearly CDD is the sum of all daily CDDs in a given year. A CZ with average temperature of 21°C on 20 days of the year and average temperature below 18°C the rest of the year will have a CDD of 60.

Second, and related to the first mechanism, large firms may have better trained managers who can both understand the change in firm exposure to climate risk and proactively invest in adaptation, including investment in energy-efficient machinery and equipment. We test this mechanism by exploiting data on participation in electricity management practices sourced from the MECS. Consistent with this mechanism, we find that higher participation rates in electricity management practices leads to a lower impact of long-run changes in temperatures on industry concentration.

Third, large firms 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 firms. 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.

Finally, large firms may be naturally better hedged to absorb weather shocks, even when they occur at higher frequency due to climate change, because they produce output in different locations, diversifying climate risk (Castro-Vincenzi, 2022; Acharya et al., 2023). To test this mechanism, we investigate whether or not the effects of long-run changes in temperature on industry concentration differ depending on the share of local small plants that are part of a multi-plant firm. We find no differential effects when sorting observations across this dimension, suggesting this specific mechanism might not be at work in our setting.

Related Literature

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

Our work is related to several recent papers studying the effect of temperature on firm outcomes. Addoum et al. (2021) show that higher temperatures affect the profitability of U.S. public firms across more than 40% of industries, and Acharya et al. (2022) show that

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

higher temperatures lead to higher bond yields and expected returns for equity. Addoum et al. (2020) document that higher temperatures do not significantly affect the sales and productivity of establishments owned by U.S. public firms.[4] Our contribution to this literature is to use micro-data representative of U.S. manufacturing plants of all sizes to document how, even in a developed economy, small plants are negatively affected by temperature shocks via energy costs and productivity. The key novel finding is that small establishments are disproportionately more affected by a warming climate, which has led to higher concentration in local labor markets over the last four decades.

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

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

A related stream of this literature focuses on the effect of industry concentration on labor market outcomes, particularly employment and wages. Theoretically, this effect is ambiguous. Higher concentration can reduce competition for workers across firms, leading to lower wages. On the other hand, reallocation of labor towards larger firms that are better managed or operate with better technologies might increase worker productivity and lead to higher wages. Previous empirical papers, including work using U.S. data, document a robust negative relationship between labor market concentration

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

and wages (Benmelech et al. 2022, Schubert et al. 2022, Arnold 2019). By contrast, we document that, over the long-run, climate-driven local industry concentration has led to higher average wages and labor productivity.

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

II Data and Background

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

II.A Data

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

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

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

for misreporting help to ensure the quality of the data.

Weather Data. We use two data sources to capture the weather and temperature-related changes in climate, as well as other climate shocks, respectively. Weather data for the contiguous U.S. over the 1950-2019 period is provided by the PRISM Climate Group. We rely on the cleaned version provided on Wolfram Schlenker's homepage.[6] The data include the daily minimum and maximum temperatures for 2.5-mile by 2.5-mile grids on the basis of a constant set of weather stations that receive a constant weight over the 1950-2019 sample period. This treatment ensures that the resulting time series of temperatures does not vary through the birth and death of stations or missing observations [see Auffhammer et al. (2013) for a discussion].

For our plant-level analysis, we measure plants' temperature exposure at the ZIP Code level. In order to obtain ZIP Code-level average daily temperatures, we first calculate the daily average temperature for each 2.5-mile by 2.5-mile grid as the equally weighted average of daily minimum temperature and daily maximum temperature reported for that grid. For each ZIP Code, we then calculate the value-weighted daily average temperature using grid points within a 20-mile radius of the ZIP Code centroid and their inverse distance to the centroid as the weight, following Heutel et al. (2021). For our CZ-level analysis, we weight all grid-level temperature observations within a commuting zone by their inverse distance to the geographic CZ midpoint. We obtain and process daily precipitation information using the same method. On the basis of the resulting respective ZIP Code-day and CZ-day temperature time series, we construct various aggregate yearly temperature measures of interest, such as number of days within certain temperature bins, as well as Cooling Degree Days ($CDDs$) and Heating Degree Days ($HDDs$).

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

Economic and Demographic Controls. Socioeconomic and demographic controls at the CZ level are based on the 1980 Census and serve as controls for pre-sample period

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

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

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

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

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

Average temperatures are predicted to continue to increase for the next decades, as confirmed by long-run projections of temperatures in the U.S. for the remainder of the 21st century. In Figure 2, we illustrate these long-run predictions utilizing the data generated by Hsiang et al. (2017). These data contain binned projections of daily weather (1981-2100) for U.S. counties using 44 different climate models. We record the number of days that fall within 1°C bins within a year (from -20°C to 40°C).[9] Next, we take the average days across all climate models for each county-year, and then calculate the mean value across all counties in a decade.

Climate modeling generally considers four Representative Concentration Pathways (RCPs) to describe different 21st-century pathways of greenhouse gas (GHG) emissions and atmospheric concentrations. The RCPs include a stringent mitigation scenario

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

[9] In order to align the arguments in this section with our later analysis, we group temperature projections into coarser bins of 3°C. In particular, we create 11 bins of 3°C each, ranging from -6°C to 26°C, plus two additional bins capturing average daily temperatures below -6°C and above 26°C.

(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 2 is the sharp spikes in the number of extremely hot days, namely days with an average temperature above 26°C. The average number of days above 26°C increases from 20 days in the 2010s to 40 days by the end of the 21st century under the optimistic scenario (RCP2.6), 60 days under the intermediate scenario (RCP4.5), and about 100 days under the worst-case scenario (RCP8.5). In other words, the number of extremely hot days is expected to double under the best-case scenario, and quintuple in the worst-case scenario.

Figure 3 illustrates the geographic distribution in the U.S. of projected changes in extremely hot days between the 1980s and the 2090s. Across all three RCPs, we observe a prevalent increase in the number of extremely hot days, with the largest increases in hot days predicted to occur in counties in southern and central states. Notably, there is also significant variation in projected hot days across counties within each state.

III Empirical Strategy

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

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

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

$$y_{ijz(s)t} = \alpha_i + \alpha_{jt} + \alpha_{st} + \sum_{\substack{b \in B \\ b \neq [9-11C)}} \beta_b D^b_{z(s)t} + \lambda X_{z(s)t} + \varepsilon_{ijz(s)t}, \tag{1}$$

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 average daily temperature is within a certain bin b. Our panel specification follows the approach of Deschênes and Greenstone (2011), which has been commonly employed in estimating temperature

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

impacts as it allows arbitrary non-linear relationships between temperature and outcome variables.[11] We divide the temperature distribution into 11 bins of 3°C each, ranging from -6°C to 26°C, plus two additional bins that capture average daily temperatures below -6°C and above 26°C, respectively. We exclude the median temperature bin 9°C-11°C in all specifications. The estimated β_b coefficients should be interpreted as the effect of an additional day with an average temperature in a certain bin relative to an additional day with average temperature of 9°C-11°C. To account for geographical correlation in the error term, we cluster standard errors at the state-level in all specifications.[12] In addition, when examining outcome variables obtained from ASM/CMF (i.e., energy costs, productivity, and employment), we estimate regressions using ASM sample weights.

Because plants have a fixed location over time, the inclusion of plant fixed effects (α_i) implies that the impact of temperature on outcomes is identified by deviations from plant-location-specific means. As such, we think of these yearly temperature shocks as random "weather" draws from the "climate" distribution in a given geographical area, and therefore as plausibly exogenous to the outcomes of interest (Dell et al., 2014). We layer additional fixed effects step-by-step to absorb potential time-varying industry and geographic dynamics that might confound our key estimates. We first include 4-digit NAICS industry fixed effects interacted with year fixed effects to absorb any aggregate trends at the industry-level experienced by U.S. manufacturing plants. We then add 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, such as 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.

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

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

Temperature shocks might be associated with precipitation or extreme weather events, and thus affect manufacturing outcomes via this association. Figure 4 reports the effect of an additional day with average temperature within each respective bin on average precipitation (Panel A) and the incidence of extreme weather events recorded in SHELDUS (Panels B to F). Perhaps unsurprisingly, additional hot days are associated with lower average precipitation, as well as lower probability of floods. Additional hot days are also mechanically associated with a higher probability of droughts and heatwaves, which are themselves defined based on the prolonged occurrence of high temperature days. The effect of temperatures on tornadoes and hurricanes are small and mostly insignificant. Given these findings, we augment equation (1) with a set of time-varying controls $X_{z(s),t}$ which include average precipitation and the occurrence of extreme weather events that are not mechanically associated with temperature, mainly hurricanes and tornadoes.

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

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

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

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

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

In equation (2), we use two parsimonious measures of temperature: cooling degree

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

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

Equation (2) includes state fixed effects, which implies that the relevant variation identifying the coefficients β_1 and β_2 originate from within-state differences in climate trends across CZs. The inclusion of state fixed effects removes any role of unobservable state-level trends. However, one 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 6.

Figure 5 reports the distribution of long-run changes in decadal averages of HDD and CDD. Panel (a) reports the distribution of these two variables in the raw data. As shown, between the 1980s and the 2010s, most U.S. CZs experience an increase in average yearly $CDDs$, or degree days above 18°C, while the changes in $HDDs$ are mostly negative. This is consistent with a significant warming trend in the U.S. during the last four decades. Panel (b) reports the distribution of long run changes in decadal averages of HDD and CDD that deviate from division averages. As shown, even net of state trends, there is still 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. Figure 6 reports the geographical distribution of these long-run changes in degree days that deviate from division-specific averages.

The key identifying assumption in equation (2) is that differential changes in degree days observed over the last four decades in each CZ are uncorrelated with other local trends that might also affect the outcomes of interest. Division fixed effects reduce the role of unobservables by removing aggregate trends across macro areas of the country. Still, a potential concern is that long-run changes in temperature might be correlated with unobservable CZ-level trends. In support of empirical approaches similar to the one

[14]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. See also the discussion by the National Oceanic and Atmospheric Service, `https://www.weather.gov/key/climate_heat_cool`.

in equation (2), previous papers in environmental economics report 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 A.2, we report the correlation between long-run changes in average temperatures and CZ-level initial characteristics, including population, per capita income, and share of college graduates among the adult population. We find no significant correlations with population 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 oiur study period, such as import competition from China (Autor et al., 2013), and find no significant correlation.

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

IV Results

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

IV.A Short-run response to temperature shocks

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

IV.A.1 Energy Costs

Manufacturing plants use electricity for production processes (e.g., to operate machinery), as well as for non-production processes (e.g., for temperature control of working environments). According to data from the Manufacturing Energy Consumption Survey reported in Figure 7, around 80% of electricity consumption by U.S. manufacturers is used in production processes and 20% is used in non-production. Figure 7 also shows that the majority of the electricity used in production processes is for machinery and equipment operations, as well as for cooling and 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, they 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 estimate equation (1) using plant-level energy costs as the outcome variable. The results are reported in Table 2 and visualized in Figure 8. We define energy costs as the monetary value of expenses in electricity and fuel divided by the value of shipments at the plant level (electricity expenses account for 75% of energy costs, fuel expenses account for 25%). We multiply all coefficients by 100 to facilitate readability, so the point estimates should be interpreted as the effect of 100 additional days in a given temperature bin relative to the omitted benchmark bins experienced by a given plant-location. We find that plants experiencing additional days with an average temperature above 18°C experience statistically significant increases in energy costs, which is consistent with previous findings in the energy literature (Engle et al., 1986). The effect is monotonically increasing in temperature bins. The magnitude of the coefficients implies that a one standard deviation increase in the number of hot days in the temperature bin between 24 °C and 27 °C (around 30 days) generates a 3% larger increase in energy costs.

We find no significant effects of additional cold days on energy costs, possibly with the exception of the coldest temperature bin. The asymmetry between the effects of additional hot days versus cold days on energy costs is prima facie surprising. One element that contributes to explain this finding is that – despite being less seasonal than residential or commercial energy consumption – industrial energy consumption displays large differences between summer and winter months. Data from the U.S. Energy Information Administration (EIA) reported in Figure 10 (a) shows that during the summer months, average consumption in kilowatthours has been 9.6% higher than during the winter months in the years since 2002. Summer is also a period of higher energy prices faced by the industrial sector in the U.S. The EIA data reported in Figure 10 (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.[15] Taken together, these facts indicate that additional hot days during the summer generate higher marginal increases in energy costs for U.S. industrial firms than additional cold days in the winter period.

Next, we investigate the effect of temperature shocks on the energy costs of small and large plants. We define plant size based on the number of employees. The results are similar depending on whether we consider small plants as those with less than 20 or 50 employees. Panels (a) and (b) of Figure 9 show that the effects of temperature shocks on energy costs are concentrated among small plants. Large manufacturing plants – and especially those with more than 50 employees – seem to be largely immune to the effects of temperature shocks on energy costs.

There are several potential explanations for this result. 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 .

Another potential explanation for the heterogeneous effects of additional hot days on energy costs is that 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.

IV.A.2 Productivity

Previous papers have documented a negative relationship between temperature and labor productivity (e.g., Graff Zivin and Neidell 2014, Heal and Park 2013, Hsiang 2010,

[15] 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.

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.

The results of estimating equation (1) when the outcome variables are different measures of productivity are reported in Table 3 and in Figure 11. We use two measures of productivity: total factor productivity (TFP) and labor productivity at the plant level, both in logs. TFP is computed as the plant-level Solow residual. Labor productivity is defined as valued added divided by the total number of employee-hours worked. Point estimates should be interpreted as the effect of 100 additional days in a given temperature bin relative to the average climate experienced at a given plant-location. We find that temperature has a negative and monotonic effect on both measures of productivity, with additional days in hotter bins leading to lower productivity. The positive effects on additional cold days are small and mostly not statistically significant, while plants experiencing additional hot days experience significant declines in productivity.

The magnitude of the coefficients imply that a one-standard-deviation increase in the number of "hot days" in the temperature bin between 24°C and 27°C (around 30 days) would generate a 1.4% decline in TFP and a 2.1% decline in labor productivity.[16]

In Figure 12, we report the results when splitting the sample between small and large plants. Independently of the threshold used to define small plants, we find that higher than usual temperatures are associated with large and significant declines in the productivity of small plants. On the other hand, the effects of temperature shocks on the productivity of large plants are small and mostly non statistically significant. Potential explanations for these heterogeneous effects of temperature shocks on plant productivity include heterogeneity in the type of labor and capital used by plants of different size. Larger plants use physical capital whose performance is less affected by abnormal temperatures, have more advanced temperature control systems (Zivin and Kahn, 2016), or

[16]Because energy is an input in production, the increase in energy costs documented above could mechanically generate a decline in value added, and thus in TFP or labor productivity measured as value added per worker. We checked this potential explanation of the productivity results by estimating equation (1) using an alternative measure of productivity in which value added is constructed without including energy among inputs. The results of this robustness test are reported in Table A.3. 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.

better insulated work environments. Differences in the type of labor force employed in large versus small plants might also play a role. For example, large plants may have employees who are more productive, more motivated, and whose performance may be less affected by temperature shocks.

We next discuss the relationship between the effects of temperature on energy costs and productivity. Higher energy expenditure increases plant costs but might also help to partly absorb the impact of temperatures on worker productivity thanks to temperature control systems. This relationship between energy expenditure and productivity is hard to test as we do not observe how manufacturing plants use energy.[17] However, the evidence presented in Figures 9 and 12 show that – within narrowly defined sectors – we observe both an increase in energy costs and a decline in productivity within small plants. Thus, another possibility is that some small plants may have less energy-efficient equipment and temperature control systems, so that higher temperatures both increase their costs and decrease their productivity.

IV.A.3 Size, Entry, and Exit

We next examine 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 enter or exit certain locations). We start by studying the effect of temperature shocks on plant size, as measured by its total number of employee-hours. The results are reported in Table 4 and visualized in Figure 13. We find no contemporaneous response to additional hot days relative to what is normally experienced by a given plant, and a positive but noisy response to additional cold days. Figure 14 shows that small and large plants are similarly non-responsive to temperature shocks on the intensive margin.

Next, we focus on the extensive margin, and in particular on the decision of a given plant to enter or exit a given ZIP Code. To this end, we use data from the LBD described in Section II.A, which tracks all manufacturing establishments, along with their location and size over time. When estimating equation (1), we define the entry of plant i in ZIP Code z during year t as a dummy equal to 1 if plant i has no employment in year $t-1$ and positive employment in year t. 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 for entry are reported in columns (1) to (4) of Table 5 and illustrated in

[17] Data from the ASM/CMF shows that the majority of energy expenditures are in electricity rather than fuel (71% vs.29%). In addition, data from the Manufacturing Energy Consumption Survey shows that, on average, about 80% of electricity is used by manufacturing plants for their production process (e.g., operating machinery and equipment, including heating, cooling and refrigeration of inputs and outputs), about 9% is used for temperature control of work environment, and another 7% for lighting.

Figure 15. We find that entry is more likely to occur in years with additional "median" temperature days, while the probability of entry declines with additional cold and hot days. As shown, higher than usual number of hot days is detrimental for the opening of a new plant in a given location, although the economic magnitude of the coefficient on the contemporaneous effects is relatively small. The magnitude of the estimated coefficients imply that a year with 100 additional days in the temperature bins above 18°C corresponds to a 1 percentage point decline in the probability of a plant opening that year. This is an economically large effect when considering the average entry rate in our sample is 0.07 (Table 1). Figure 16 shows that the effects of temperature shocks on entry are concentrated on plants with less than 20 or 50 employees. The effects on large plants follow a pattern similar to small plants across temperature bins, but are smaller in magnitude and noisier.

The results for exit are reported in columns (5) to (8) of Table 5 and illustrated in Figure 17. 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. We find that the majority of exit events in the LBD occur after plants decrease in size and thus enter into the category of small plants. This implies that when studying the heterogeneous effects of temperature shocks on exit by plant size, we can only estimate the saturated model described in equation (1) for small plants. These results are reported in Figure 18, and show a similar pattern as in Figure 17.

IV.A.4 Robustness Tests

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

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

manufacturing of food, beverage and tobacco products). Results are robust to this sample restriction.

IV.B Long-run response to changes in temperature

The short-run response to temperature shocks documented in Section IV.A indicates 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, possibly with the exception of a lower likelihood of entering. It is plausible that key industrial decisions such as reducing the size of an existing plant or exiting a given market are not driven by yearly weather shocks, especially if such shocks are interpreted as idiosyncratic and therefore likely to revert. On the other hand, the cumulative effect of several years of hotter than usual weather might push managers to respond on these margins. This is because a series of deviations from past temperatures might indicate a shift in the climate distribution from which weather events are drawn in a given geographical area.

To investigate the response to long-run changes in average temperatures in a given CZ we estimate equation (2) described in section III.B. This equation relates long-run changes in manufacturing activity to long-run changes in average temperatures between the 1980s and the 2010s. As discussed in section II.B, the U.S. experienced a large increase in average temperatures between the 1980s and 2010s, with substantial variation even across CZ within the same areas of the country. Because the short-run effects indicate that there are significant heterogeneous effects of temperature shocks across plants of different size, we investigate the effects of long-run changes in average temperatures separately for small versus large plants.

IV.B.1 Number of Plants and Employment

We start by studying the effect of long-run changes in temperature on long-run changes in the number and employment in small vs large plants in a given CZ. The results are visualized in Figure 19 and reported in Table 6.

The point estimates reported in columns (1) and (2) of Table 6 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 that in the 2010s had a standard deviation higher increase in temperature – about 60 degree days per year above 18°C – relative to the 1980s experienced a 3% to 4% percent larger decline in the number of manufacturing plants with less than 20 employees. This effect is not statistically significant at standard levels when we control for the set of initial CZ characteristics described in Section III.B, although its magnitude remains relatively stable. 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 (i.e. small plants becoming 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 19 and reported in columns (5) to (8) of Table 6. We find negative and significant effects of long-run changes in average temperatures on employment in small plants. The estimated coefficient in column (6) of Panel A indicates that CZs that in the 2010s had a standard deviation higher increase in temperature – about 60 degree days per year above 18°C – relative to the 1980s experienced a 5% larger decline in the number of workers employed by manufacturing plants with less than 20 employees. The point estimates on the number of workers in large plants are positive, indicating that while the number of large plants does not increase, these plants are likely able to absorb the labor force lost by smaller manufacturing establishments.[18]

Finally, in Table 7 we document the overall effect of long-run increases in temperatures on the total number of plants, overall employment, and average plant size in a given CZ. We find negative and significant effects of long-run increases in temperature on the total number of plants: CZs that in the 2010s had a standard deviation higher increase in temperature relative to the 1980s experienced a 4% larger decline in total number of plants. We find no significant effects of long-run temperature changes on total employment, leading to a positive and significant effect on the average plant size. Overall, these results indicate that CZs with faster warming temperatures experienced no significant changes in total employment but a reallocation of production from small to large plants. This led to a 6% higher increase in average plant size for a standard deviation higher increase in average temperatures over the last four decades.

IV.B.2 Concentration of Manufacturing Activity

The results in Tables 6 and 7 indicate that, over the long run, areas getting warmer at a faster pace experienced larger declines in the number of small plants and no effect on the number of large plants. In this section, we study the impact of long-run changes in temperature on local concentration in manufacturing activity.

We bring the analysis at 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

[18] Table A.6 replicates the results presented in Table 6 splitting plants into small versus large using the 50 employees thresholds.

the amount of concentration in the employment share across plants, with higher values indicating higher concentration.

The results are reported in Table 8. 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 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.[19]

V Mechanisms

Our key finding that faster warming has 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-sector level in which the measure of long-run changes in temperature $\Delta CDD_{c(d)}$ is interacted with variables capturing exposure to different mechanisms. We consider four potential mechanisms: energy prices, managerial skills, access to finance, and ability to hedge across locations.

V.A Energy prices

Small firms face higher prices per unit of energy used than large firms. The latest U.S. Manufacturing Energy Consumption Survey, which was run in 2018 on a nationally representative sample of manufacturing establishments, shows that establishments with fewer than 50 employees face electricity prices (in USD per m BTU) that are 33% higher than those faced by manufacturing establishments with 50 employees and above.[20] The reason is that large manufacturing firms 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

[19]In Table A.7, we report the effect of long-run changes in average temperatures on average wages and labor productivity. The results show that manufacturing sectors in CZs that got relatively warmer in the last four decades experienced an increase in both average wages and labor productivity. These results are consistent with climate change generating a reallocation of labor towards larger firms that are better managed or operate with better technologies, thus leading to higher worker productivity and higher average wages for local workers. We think of these results as only suggestive evidence because our data does not allow to properly control for worker characteristics in the computation of average wages.

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

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 firms than for large firms 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 firms. This is a potential mechanism behind the relative decline in both the number and the employment share of small firms in regions that experienced faster warming during the last four decades.

To test this mechanism, we interact long-run changes in temperature at CZ level with 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 20, average electricity prices per unit of energy are highly correlated with the price gap between small and large firms at the division-year level. Notice that, although MECS reports information on electricity prices for firms with employment above versus below 50 employees, this information is only available aggregated at the Census division level (9 divisions), providing limited cross-sectional variation. Thus, when testing this mechanism, we exploit variation in baseline average electricity prices, which is available at the industry-Census region level.[21]

The results are in Panel A of Table 9 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 given increase in long-run temperatures, industry-regions in the top tercile of energy costs experience a 2.2 percentage points larger increase in the share of employment in the top 5 largest plants and a 10 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.

V.B Managerial skills

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

Second, previous work also establish that better managed firms are less energy inten-

[21] Ideally, we would like to use a baseline measure of electricity prices faced by firms 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.

sive 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 electricity management practices at the industry-level from the Manufacturing Energy Consumption Survey (MECS) 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 9. As shown, we find that higher participation rates in electricity management leads 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 electricity management practices relative to those in the first tercile.

V.C Access to finance

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

To test this mechanism, we exploit variation in the density of bank branches per capita across CZs as a proxy for local financial development and ability to access bank financing for small and medium firms. 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 9. 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 firm 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.D Hedging across locations

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

In order to test this mechanism, we investigate whether the effects of long-run changes in temperature on concentration differ depending on whether local small plants are single-unit firms or part of a multi-plant firm. The hedging mechanism described above would imply that small plants that are part of a multi-unit firm should be better able to cope with the negative effects of long-run increases in temperature, leading to a lower impact of higher temperatures on local industry concentration. We use data from the U.S. Census Bureau and sort industry-CZs by the share of small plants that are part of multi-unit firms in the 1980s (decadal average). The results are reported in Panel D of Table 9. We find no differential effect of long-run changes in temperature on concentration depending on whether local small plants are part of multi-unit firms, suggesting this mechanism does not seem to be at work in our setting.

VI 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 firms being better equipped to adapt to climate change. Evidence indicates that differences in costs per unit of energy, managerial skills, and, to some degree, 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 employment within large firms 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. First, on average, we find that higher increases in average temperature lead to both higher concentration of employment in large firms and higher local average wages. Second, the presence of large firms 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 firms but no significant changes in the overall employment at the county level. On the other hand, the differential effect of temperature on small firms 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 become a barrier to entrepreneurship in certain regions. All these are important avenues for future research.

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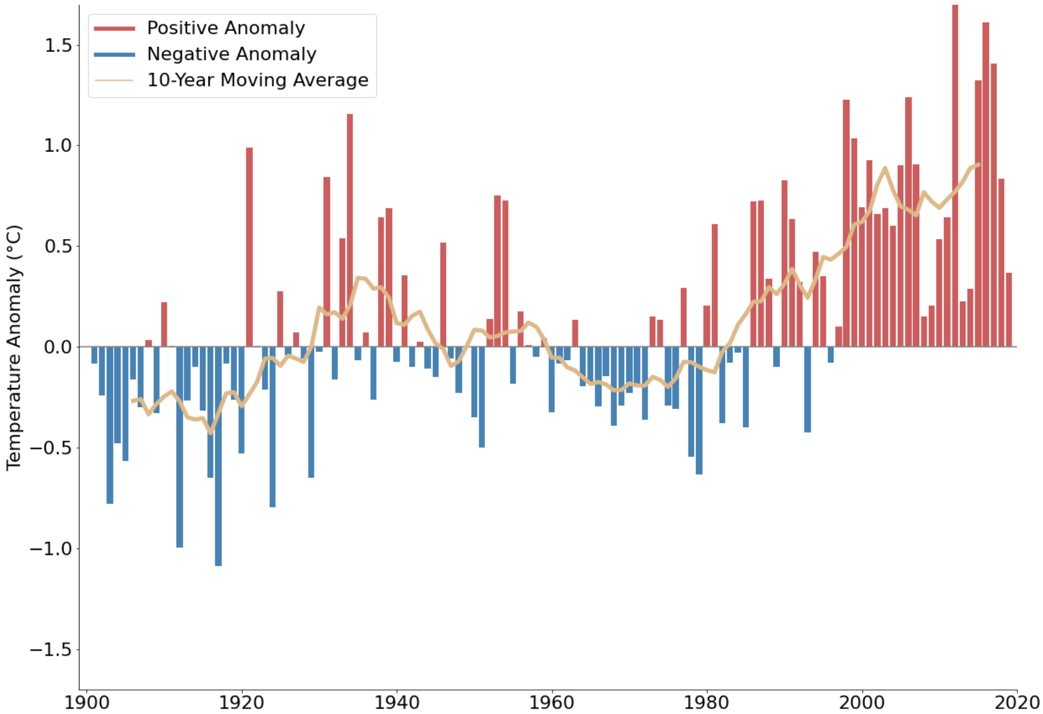
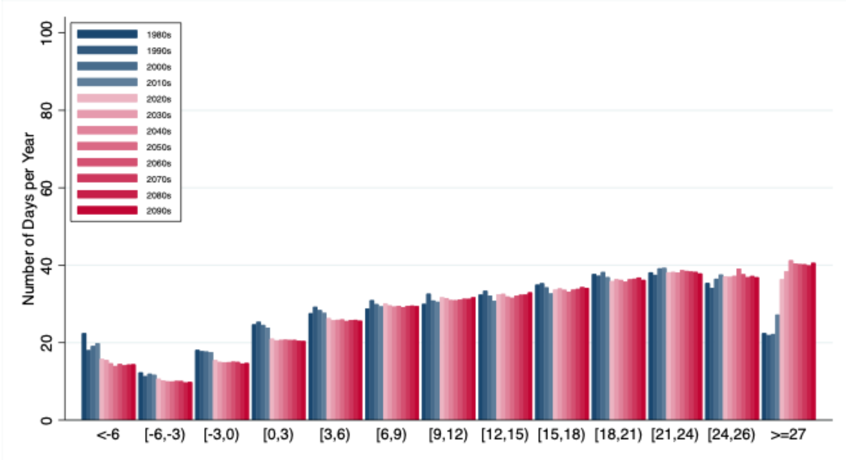
Figure 1: Temperature trend in the U.S.



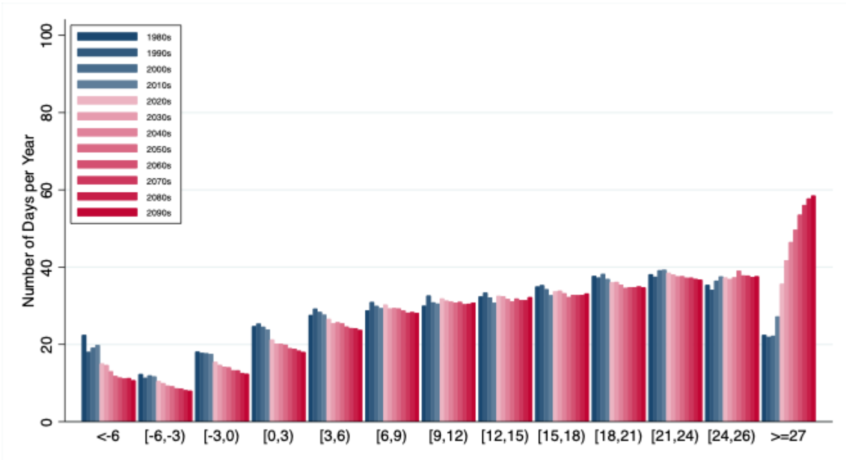
The figure shows annual and decadal temperature dynamics over the 1901 to 2019 period on the basis of temperature data obtained from the National Oceanic and Atmospheric Administration (NOAA). The underlying data covers 48 contiguous states. Annual anomalies (the bars) are defined as the difference between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

Figure 2: Distribution of temperature days by bin over time

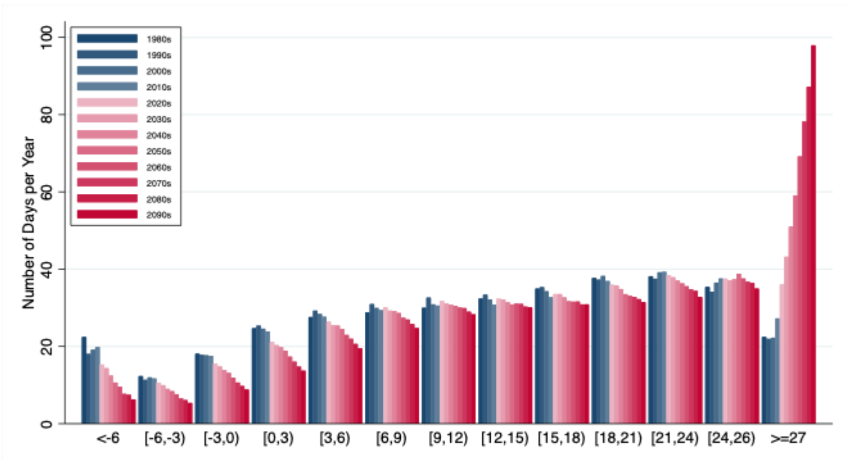
Panel A: Stringent Scenario (RCP 2.6)



Panel B: Intermediate Scenario (RCP 4.5)



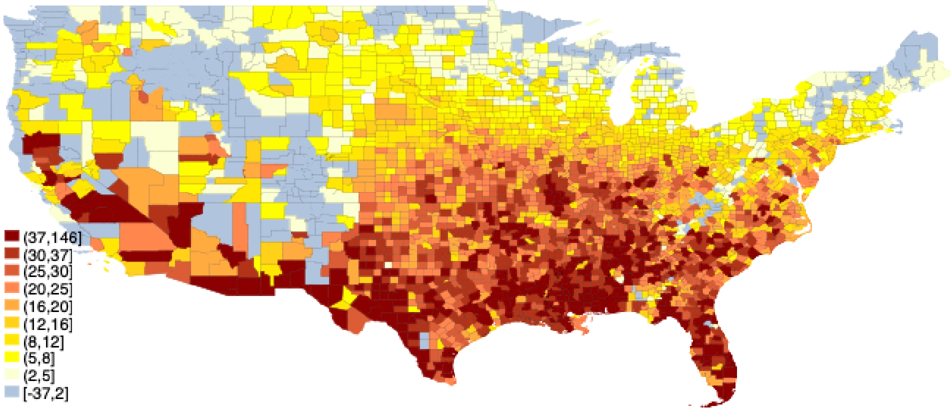
Panel C: High Greenhouse Gas Emission Scenario (RCP 8.5)



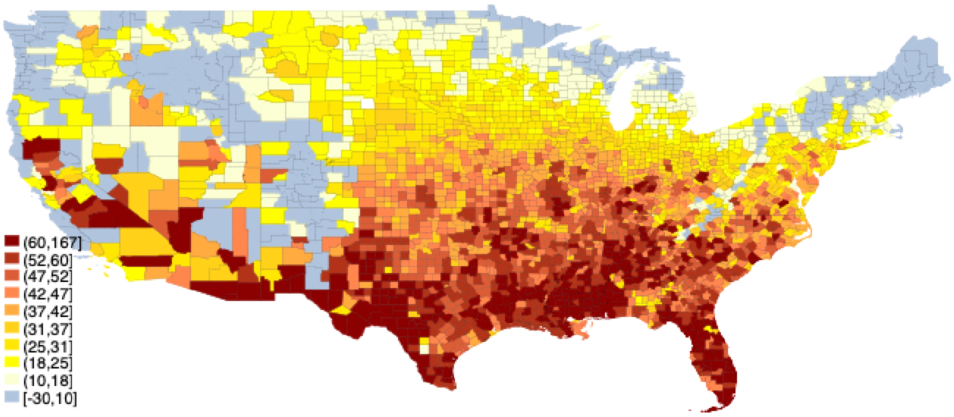
The figure shows decadal U.S. long-run temperature projections on the basis of big data generated by Hsiang et al. (2017) for the 1980s to 2090s. The underlying data are based on 44 climate models. Shown are projections under three different Representative Concentration Pathways (RCPs) used to describe 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 for respective 3°C bins (x-axis) for a range of decades (color-coded bar), averaged across U.S. counties.

FIGURE 3: PROJECTED CHANGES IN THE NUMBER OF DAYS ABOVE 26°C BETWEEN THE 1980S AND THE 2090S

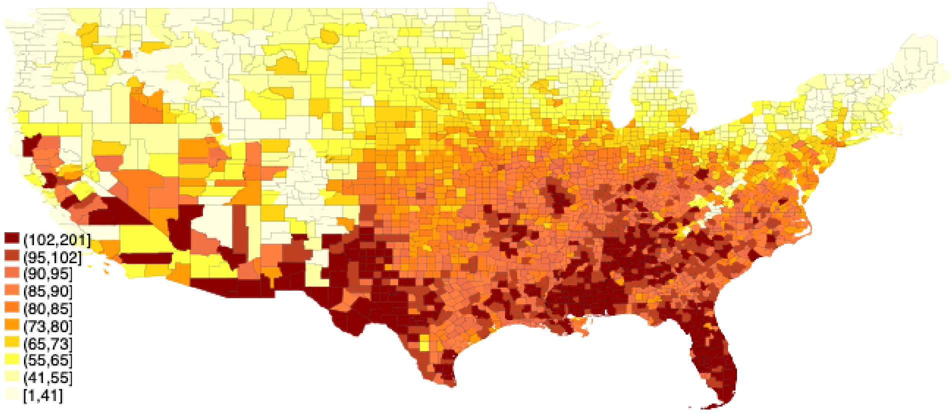
Panel A: Stringent Scenario (RCP 2.6)



Panel B: Intermediate Scenario (RCP 4.5)

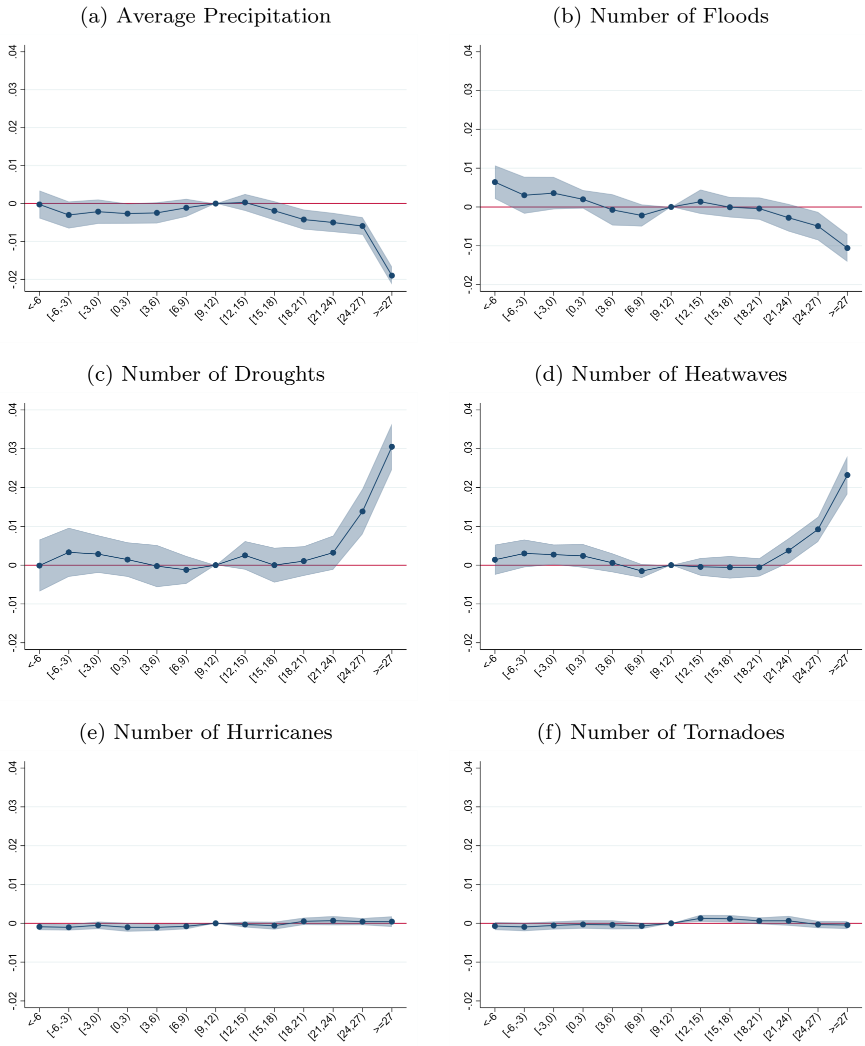


Panel C: High Greenhouse Gas Emission Scenario (RCP 8.5)



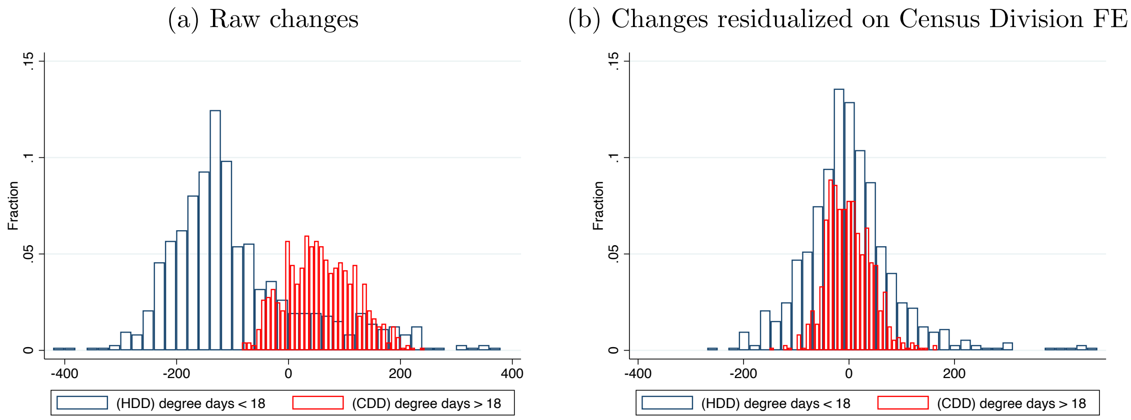
The figure shows long-run temperature projections by U.S. county for the contiguous 48 states on the basis of big data generated by Hsiang et al. (2017) for the 1980s to 2090s. The underlying data are based on 44 climate models. Shown is the county-level change between the average projected number of days above 26°C in the 2090s and the average number of days above 26°C in the 1980s for a stringent mitigation scenario (Panel A), an intermediate scenario (Panel B), and a scenario with very high GHG emissions (Panel C).

Figure 4: Effects of long-run changes in temperature on precipitation and extreme weather events



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).

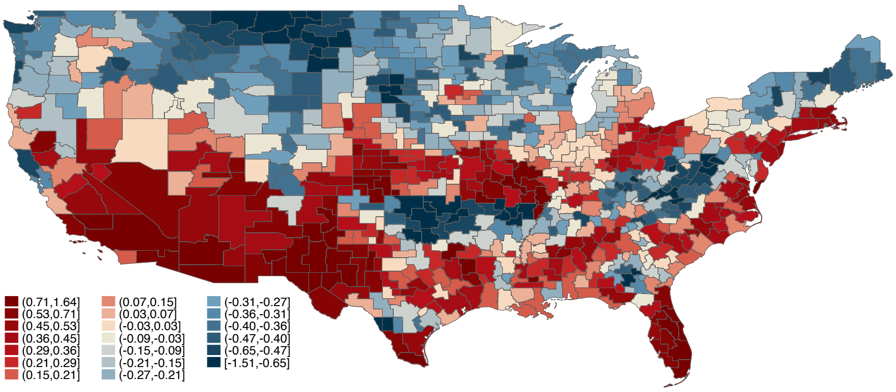
Figure 5: Distribution of the long-run changes in degree days above and below 18°C



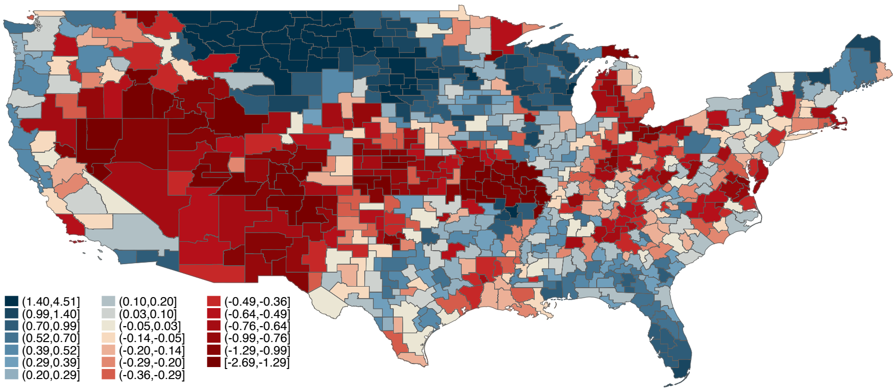
The figure shows the distribution of changes in heating degree days (HDD; blue) and cooling degree days (CDDs; red) from the 1980s to the 2010s at the commuting zone level. A daily CDD is the difference in degrees between the average daily temperature and 18°C conditional on the average daily temperature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

Figure 6: Geographic distribution of long-run changes in degree days above and below 18°C

(a) Δ (degree days > 18°C or CDDs)

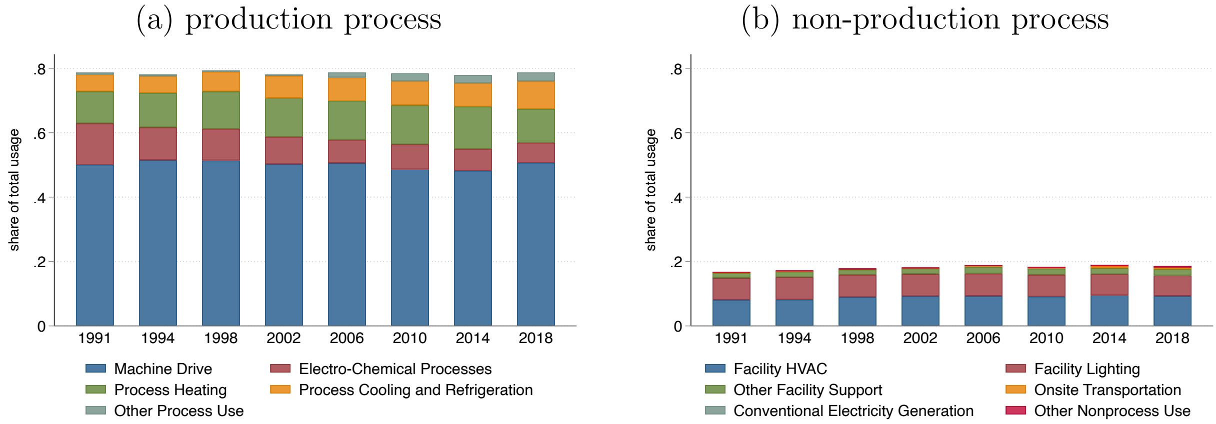


(b) Δ (degree days < 18°C or HDDs)



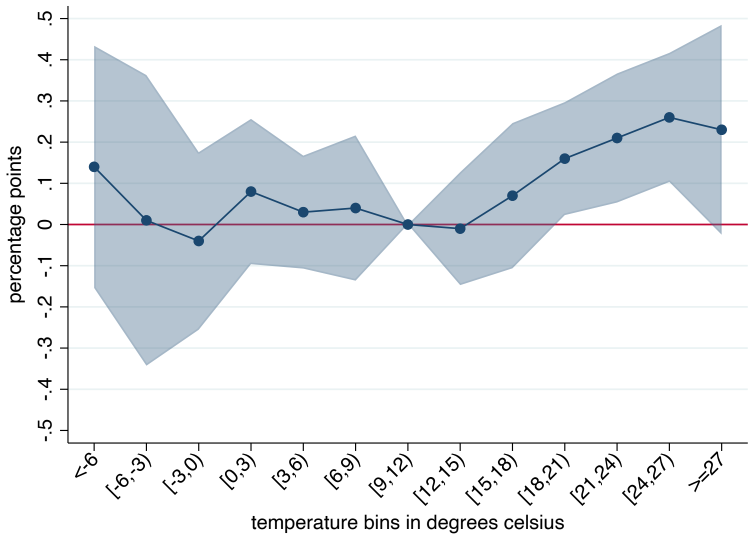
The figure shows changes in Cooling Degree Days (CDDs, Panel A) and Heating Degree Days (HDDs, Panel B) between the 1980s and the 2010s by commuting zone relative to average Census division changes. A daily Cooling Degree Day (CDD) is the difference in degrees between the average daily temperature and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

Figure 7: Electricity Usage by U.S. Manufacturing Plants



Data source: Manufacturing Energy Consumption Survey, all waves.

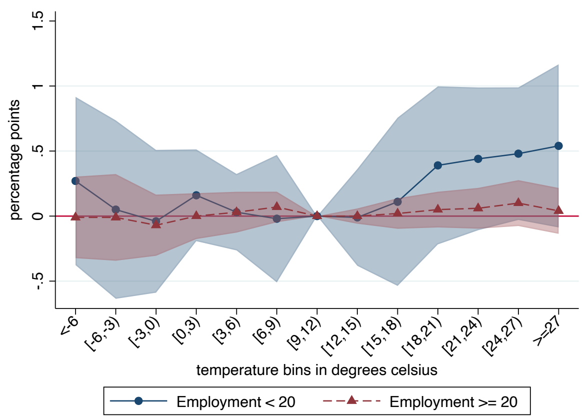
Figure 8: Short-run effect of temperature on energy costs (as a percentage of the total value of shipments)



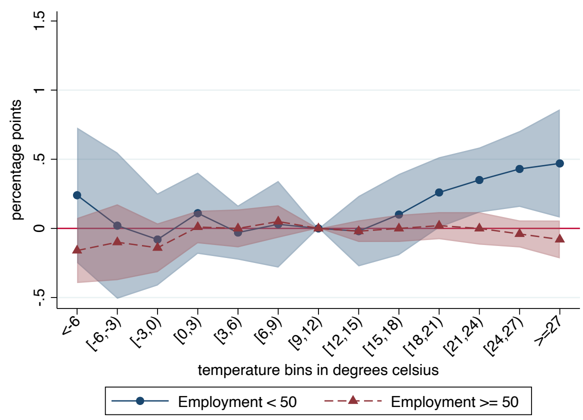
The figure shows the point estimates and the 95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on energy costs divided by total value of shipments. The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days 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 [9°C,12°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 9: Heterogeneous short-run effects of temperature on energy costs (as percentage of total value of shipments)

(a) Split at Employment=20



(b) Split at Employment=50

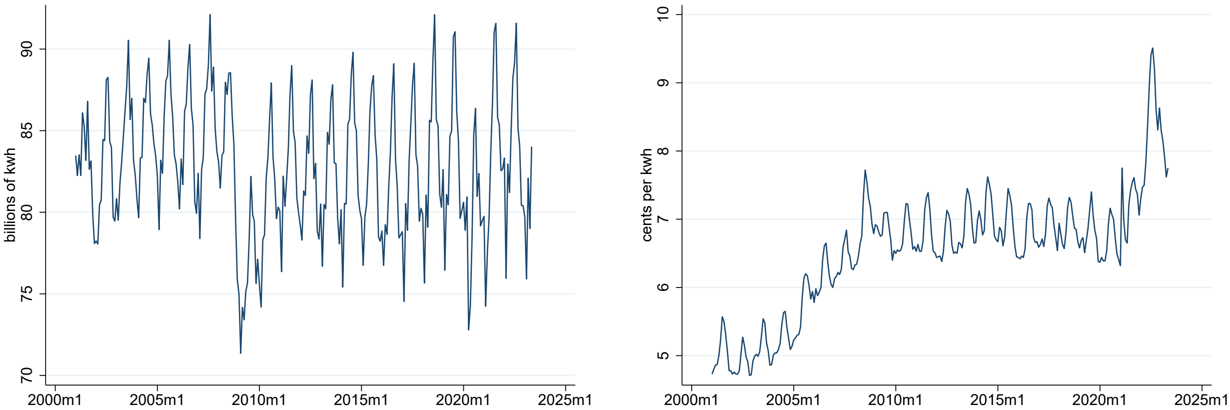


The figure shows point estimates and 95% confidence intervals when estimating the specification used in Figure 8 by plant size. In Panel A, the sample is split into plants with strictly fewer than 20 employees (blue) and more than 20 employees (red). In Panel B, the size cut-off is 50 employees.

Figure 10: Seasonality in industrial electricity demand and prices

(a) Electricity sales, industrial sector

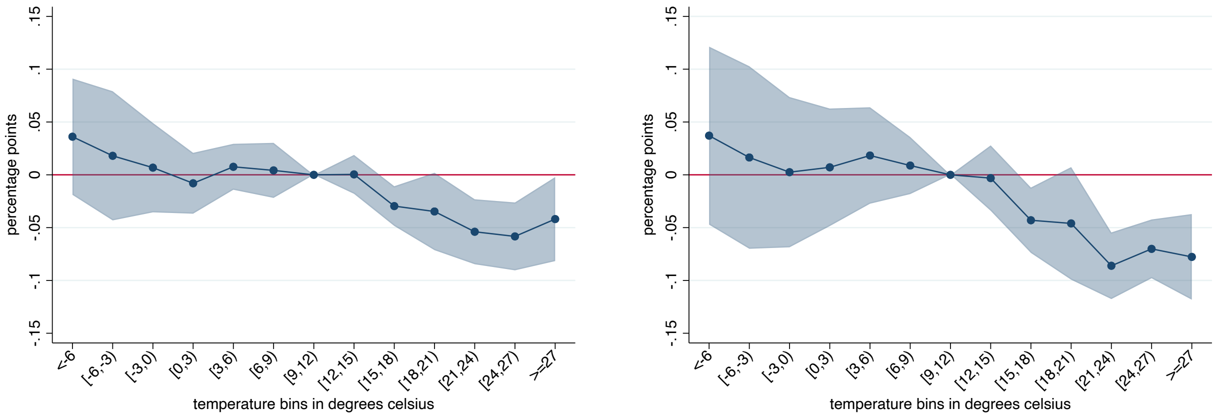
(b) Electricity prices, industrial sector



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

Figure 11: Short-run effect of temperature on productivity

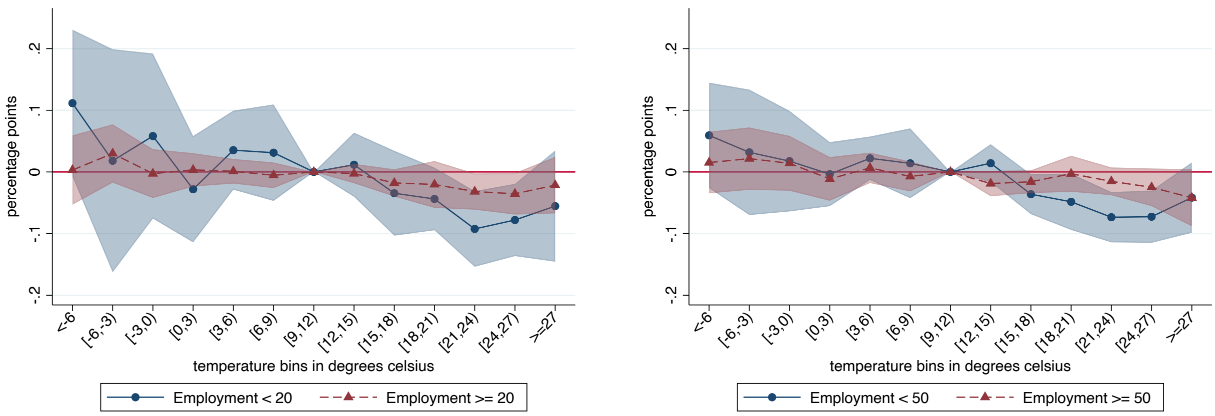
(a) Log(TFP) (b) Log(Value Added/Total Working Hours)



The figure shows the point estimates and the 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 over total working hours (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 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 [9°C,12°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.

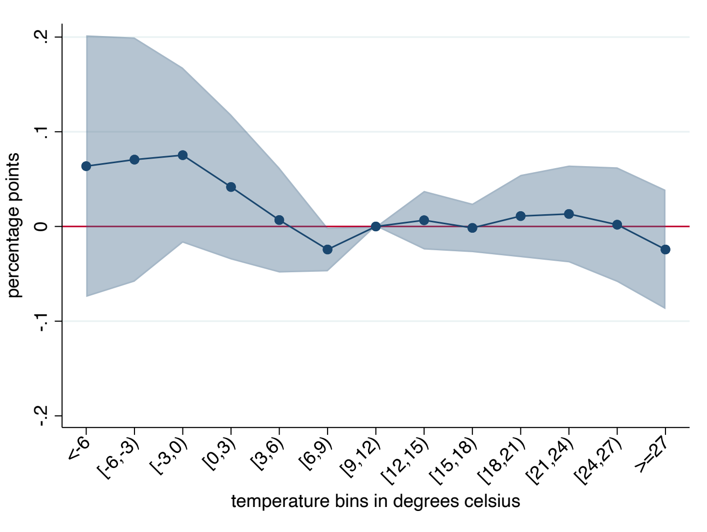
Figure 12: Heterogeneous short-run effects of temperature on Log(TFP)

(a) Split at employment=20 (b) Split at employment=50



The figure shows point estimates and 95% confidence intervals when estimating the specification used in Figure 11, Panel A (natural logarithm of TFP) by plant size. In Panel A, the sample is split into plants with strictly fewer than 20 employees (blue) and more than 20 employees (red). In Panel B, the size cut-off is 50 employees.

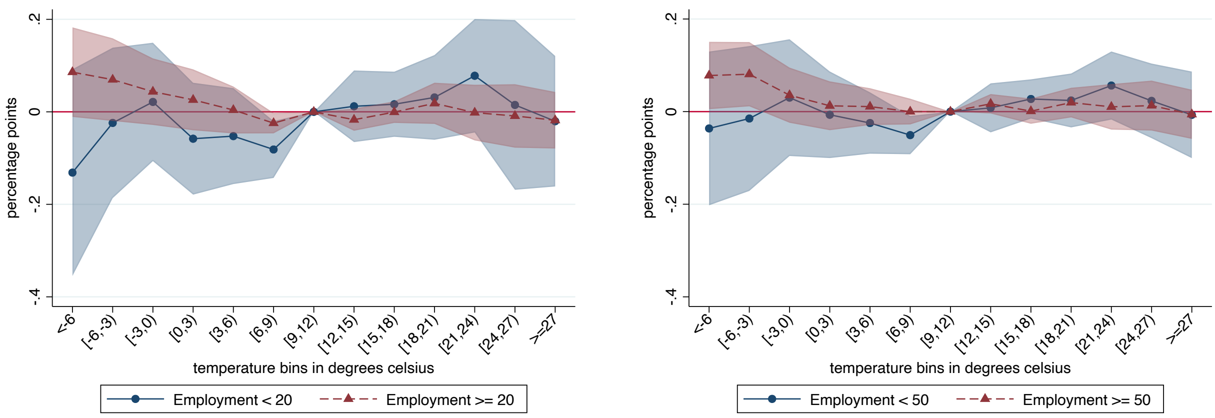
Figure 13: Short-run effect of temperature on log(total employee hours)



The figure shows the point estimates and the 95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on the natural logarithm of total hours worked. 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 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 [9°C,12°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.

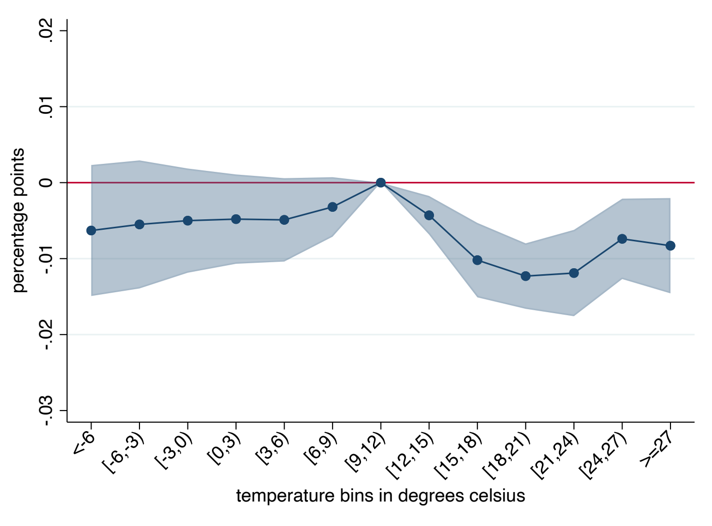
Figure 14: Heterogeneous short-run effects of temperature on log(total employee hours)

(a) Employment $<$ 20 (b) Employment $<$ 50



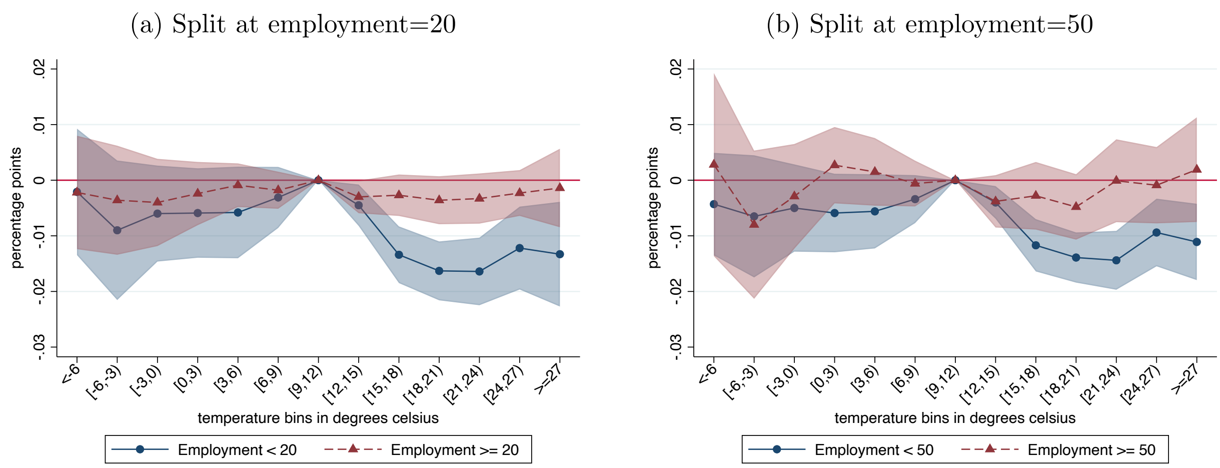
The figure shows point estimates and 95% confidence intervals when estimating the specification used in Figure 13 by plant size. In Panel A, the sample is split into plants with strictly fewer than 20 employees (blue) and more than 20 employees (red). In Panel B, the size cut-off is 50 employees.

Figure 15: Short-run effect of temperature on entry



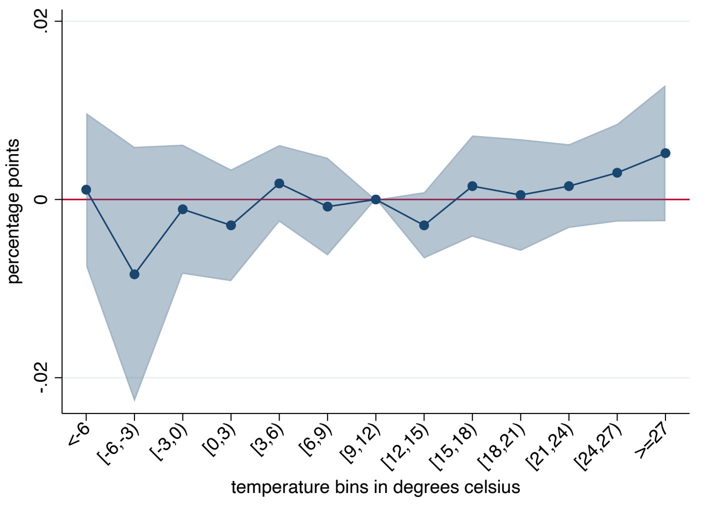
The figure shows the point estimates and the 95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on entry. The analysis is at the plant-year level and the sample period comprises 1977 to 2018. The coefficients shown along the x-axis represent the number of days 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 [9°C,12°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.

Figure 16: Heterogeneous short-run effects of temperature on entry



The figure shows point estimates and 95% confidence intervals when estimating the specification used in Figure 15 by plant size. In Panel A, the sample is split into plants with strictly fewer than 20 employees (blue) and more than 20 employees (red). In Panel B, the size cut-off is 50 employees.

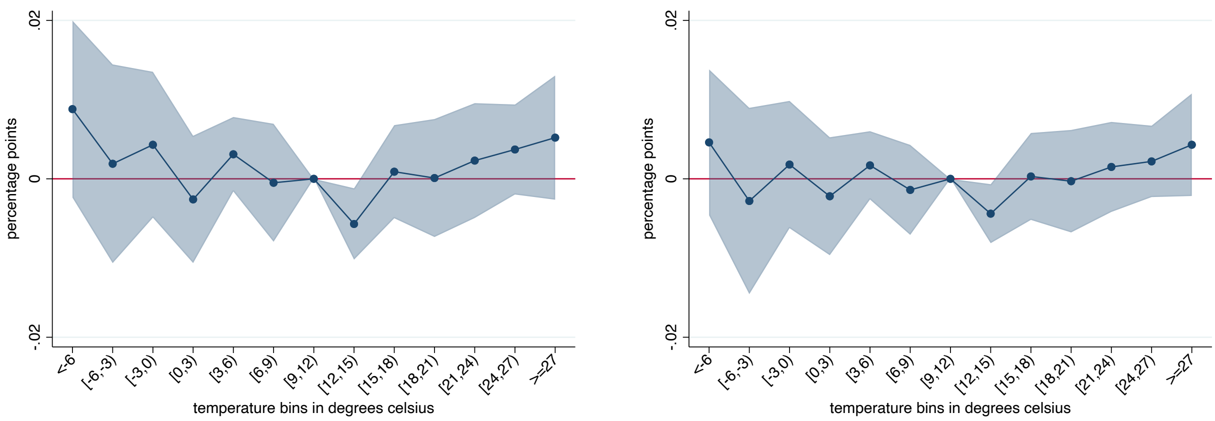
Figure 17: Short-run effect of temperature on exit



The figure shows the point estimates and the 95% confidence intervals when using the panel data approach described in equation (1) to estimate the short-run effect of temperature on exit. 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 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 [9°C,12°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.

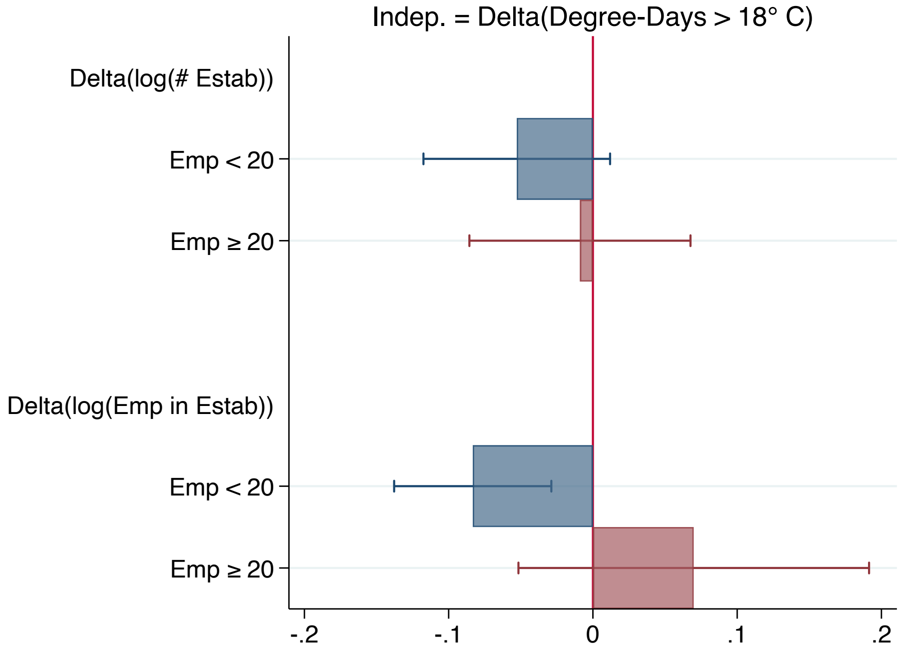
Figure 18: Heterogeneous short-run effects of temperature on exit

(a) Employment < 20 (b) Employment < 50



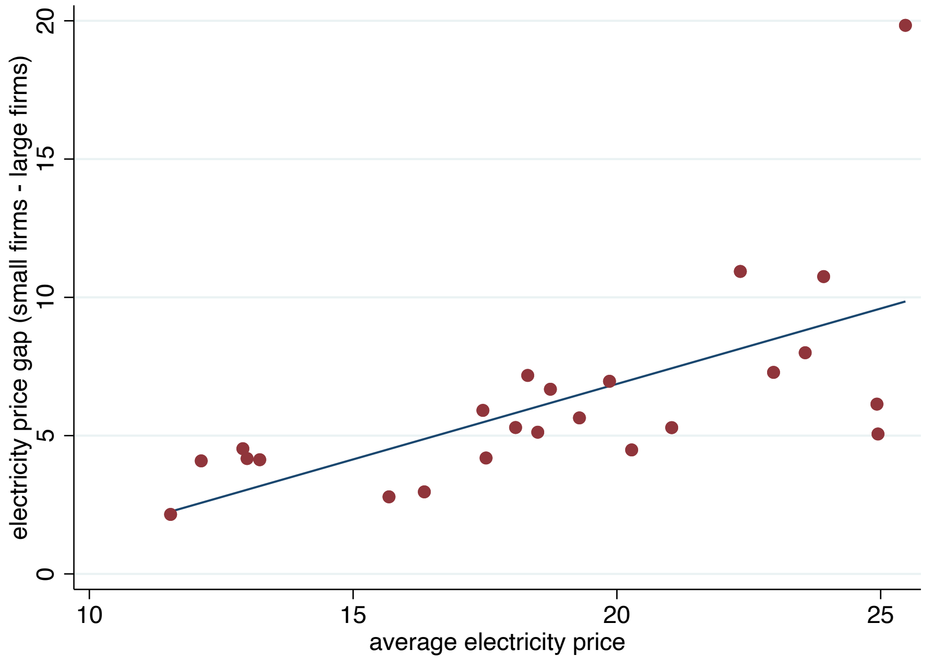
The figure shows point estimates and 95% confidence intervals when estimating the specification used in Figure 17 by plant size. In Panel A, the sample is based on plants strictly fewer than 20 employees. In Panel B, the size cut-off is 50 employees.

FIGURE 19: HETEROGENEOUS LONG-RUN EFFECTS OF TEMPERATURE ON NUMBER OF PLANTS AND EMPLOYMENT



The figure illustrates the results of Table 6 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 number of employees across plant sizes, defined as strictly fewer than 20 employees (blue) and more than 20 employees (red). The top panel shows results for the change in the natural logarithm of the average yearly number of plants between the 2010s and the 1980s. Similarly, 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 CDDs between the 2010s and the 1980s at the commuting zone level. Included throughout are Census Division fixed effects and commuting-zone-level controls for long-run changes in average precipitation, 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, changes in exposure to the China shock between 1990 and 2007 (Autor et al. 2013), and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are clustered at the state level.

Figure 20: Correlation between average electricity price and the price gap between small and large firms



The figure shows the positive correlation between the average electricity price and the price gap between small and large firms 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 firms with an employment under 50 people and those for larger firms.

Table 1: Summary Statistics

Variables	N	Mean	Std. Dev.
Panel A: ASM & CMF Sample			
Energy/Total Value of Shipments	1922000	0.022	0.0291
Log(TFP)	1922000	1.85	0.56
Log(Value-Added / Total Hours Worked)	1922000	3.472	0.912
Log(Total Hours Worked)	1922000	5.193	1.395
T < -6°C	1922000	15.34	19.09
-6°C ≤ T < -3°C	1922000	10.92	9.622
-3°C ≤ T < 0°C	1922000	16.48	12.41
0°C ≤ T < 3°C	1922000	22.57	14.14
3°C ≤ T < 6°C	1922000	26.47	13.69
6°C ≤ T < 9°C	1922000	29.4	12.76
12°C ≤ T < 15°C	1922000	35.66	14.14
15°C ≤ T < 18°C	1922000	38.51	15.82
18°C ≤ T < 21°C	1922000	41.95	14.39
21°C ≤ T < 24°C	1922000	42.36	15.01
24°C ≤ T < 27°C	1922000	32.96	22.25
T ≥ 27°C	1922000	20.02	30.94
Panel B: LBD Sample			
Exit	13590000	0.0754	0.264
Entry	13590000	0.0727	0.26
T < -6°C	13590000	14.21	18.59
-6°C ≤ T < -3°C	13590000	10.47	9.739
-3°C ≤ T < 0°C	13590000	15.77	12.67
0°C ≤ T < 3°C	13590000	21.65	14.83
3°C ≤ T < 6°C	13590000	25.68	14.97
6°C ≤ T < 9°C	13590000	28.87	14.14
12°C ≤ T < 15°C	13590000	36.95	16.12
15°C ≤ T < 18°C	13590000	40.04	17.95
18°C ≤ T < 21°C	13590000	42.79	15.84
21°C ≤ T < 24°C	13590000	42.74	16.59
24°C ≤ T < 27°C	13590000	32.28	23.24
T ≥ 27°C	13590000	20.81	33.02
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	-0.020	0.2958
Δ Log(Emp.)	700	-0.215	0.540
Δ Log(Avg. Size of Estab.)	700	-0.198	0.431
Δ Log(# Estab. of Size < 20)	700	0.026	0.288
Δ Log(# Estab. of Size ≥ 20)	700	-0.095	0.414
Δ Log(Emp. in Estab. of Size < 20)	700	-0.007	0.334
Δ Log(Emp. in Estab. of Size ≥ 20)	700	-0.238	0.536
Δ Log(# Estab. of Size < 50)	650	0.022	0.269
Δ Log(# Estab. of Size ≥ 50)	650	-0.187	0.434
Δ Log(Emp. in Estab. of Size < 50)	650	-0.001	0.329
Δ Log(Emp. in Estab. of Size ≥ 50)	650	-0.272	0.554
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	-0.004	0.535

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 county level (Panel C). Variable definitions are in Appendix Table A.1.

Table 2: Short-run effect of temperature on energy costs

Dep. Var.	Energy Costs/TVS		
	(1)	(2)	(3)
T < -6°C	0.0008	0.001	0.0014
	(0.0006)	(0.0008)	(0.0015)
-6°C ≤ T < -3°C	0.0008	0.0008	0.0001
	(0.0009)	(0.0009)	(0.0018)
-3°C ≤ T < 0°C	0.0000	-0.0002	-0.0004
	(0.0006)	(0.0006)	(0.0011)
0°C ≤ T < 3°C	0.0008	0.0009	0.0008
	(0.0005)	(0.0006)	(0.0009)
3°C ≤ T < 6°C	0.0003	0.0008	0.0003
	(0.0006)	(0.0006)	(0.0007)
6°C ≤ T < 9°C	0.0003	0.0005	0.0004
	(0.0007)	(0.0007)	(0.0009)
12°C ≤ T < 15°C	0.0009**	0.0007	-0.0001
	(0.0004)	(0.0006)	(0.0007)
15°C ≤ T < 18°C	0.0012**	0.001	0.0007
	(0.0004)	(0.0007)	(0.0009)
18°C ≤ T < 21°C	0.0014***	0.0015**	0.0016**
	(0.0005)	(0.0006)	(0.0007)
21°C ≤ T < 24°C	0.0015***	0.0018***	0.0021***
	(0.0005)	(0.0006)	(0.0008)
24°C ≤ T < 27°C	0.0013***	0.0018***	0.0026***
	(0.0004)	(0.0005)	(0.0008)
T ≥ 27°C	0.0008	0.0015**	0.0023*
	(0.0005)	(0.0007)	(0.0013)
Obs	1922000	1922000	1922000
R-squared	0.793	0.794	0.795
Establishment FE	yes	yes	yes
NAICS4-Year FE	yes	yes	yes
Census Division-year FE		yes	
State-year FE			yes
Extreme weather controls		yes	yes

Notes: We use 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. The analysis is at the plant-year level and the sample period is 1977 to 2018. The coefficients of interest represent the number of days in each respective temperature bin (β_b in equation (1)) in a given year in a plant's ZIP Code. The number of days 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. 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 effect of temperature on productivity

Dep. Var.	Log(TFP)			Log(Value-Added/Total Hours Worked)		
	(1)	(2)	(3)	(4)	(5)	(6)
T < -6°C	-0.0024	0.0221	0.0361	0.0068	0.0081	0.0371
	(0.0107)	(0.0161)	(0.0281)	(0.0176)	(0.0243)	(0.0430)
-6°C ≤ T < -3°C	-0.0147	0.0019	0.018	-0.0237	-0.0088	0.0164
	(0.0136)	(0.0200)	(0.0312)	(0.0212)	(0.0294)	(0.0441)
-3°C ≤ T < 0°C	-0.0029	-0.0001	0.0068	-0.0025	-0.0082	0.0025
	(0.0133)	(0.0166)	(0.0216)	(0.0192)	(0.0231)	(0.0363)
0°C ≤ T < 3°C	-0.0033	-0.0028	-0.008	0.0027	0.0055	0.0071
	(0.0090)	(0.0117)	(0.0147)	(0.0128)	(0.0163)	(0.0284)
3°C ≤ T < 6°C	0.0012	0.0026	0.0076	0.0012	0.0152	0.0183
	(0.0096)	(0.0109)	(0.0111)	(0.0137)	(0.0182)	(0.0233)
6°C ≤ T < 9°C	-0.0107	-0.0007	0.0042	-0.0081	0.0091	0.0088
	(0.0104)	(0.0092)	(0.0133)	(0.0126)	(0.0119)	(0.0138)
12°C ≤ T < 15°C	-0.0073	-0.0044	0.0004	-0.0007	-0.0042	-0.0031
	(0.0086)	(0.0092)	(0.0094)	(0.0129)	(0.0133)	(0.0158)
15°C ≤ T < 18°C	-0.0012	-0.0145	-0.0296***	-0.0131	-0.0277**	-0.0430***
	(0.0109)	(0.0088)	(0.0096)	(0.0121)	(0.0137)	(0.0158)
18°C ≤ T < 21°C	0.0004	-0.0149	-0.0347*	-0.0027	-0.0254	-0.0460*
	(0.0093)	(0.0139)	(0.0187)	(0.0122)	(0.0208)	(0.0272)
21°C ≤ T < 24°C	-0.0086	-0.0311***	-0.0539***	-0.0310**	-0.0596***	-0.0861***
	(0.0097)	(0.0105)	(0.0157)	(0.0141)	(0.0133)	(0.0161)
24°C ≤ T < 27°C	-0.0101	-0.0341***	-0.0583***	-0.0246*	-0.0461***	-0.0701***
	(0.0097)	(0.0101)	(0.0164)	(0.0132)	(0.0136)	(0.0142)
T ≥ 27°C	0.0068	-0.0179	-0.0419**	-0.0048	-0.0346**	-0.0777***
	(0.0088)	(0.0128)	(0.0203)	(0.0121)	(0.0151)	(0.0207)
Obs	1922000	1922000	1922000	1922000	1922000	1922000
R-squared	0.785	0.786	0.787	0.781	0.781	0.782
Establishment FE	yes	yes	yes	yes	yes	yes
NAICS4-Year FE	yes	yes	yes	yes	yes	yes
Census Division-year FE		yes			yes	
State-year FE			yes			yes
Extreme Weather controls		yes	yes		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 (TFP; columns (1)-(4)) and the natural logarithm of value added divided by total number of hours worked (columns (5)-(8)). The analysis is at the plant-year level and the sample period comprises 1977-2018. The shown coefficients of interest represent the number of days in each respective temperature bin (β_b in equation (1)) in a given year in a plant's zip code. The number of days 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. 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: Short-run effect of temperature on employment

Dep. Var.	Log(Total Hours Worked)		
	(1)	(2)	(3)
T < -6°C	0.0484**	0.0569*	0.0637
	(0.0181)	(0.0329)	(0.0705)
-6°C ≤ T < -3°C	0.0382	0.0422	0.0706
	(0.0339)	(0.0381)	(0.0658)
-3°C ≤ T < 0°C	0.0447**	0.0457	0.0753
	(0.0214)	(0.0277)	(0.0472)
0°C ≤ T < 3°C	0.0303	0.0228	0.0417
	(0.0199)	(0.0191)	(0.0391)
3°C ≤ T < 6°C	0.006	-0.0161	0.0068
	(0.0150)	(0.0163)	(0.0283)
6°C ≤ T < 9°C	0.0033	-0.0191*	-0.0243**
	(0.0119)	(0.0114)	(0.0118)
12°C ≤ T < 15°C	-0.0022	0.0063	0.0066
	(0.0191)	(0.0143)	(0.0158)
15°C ≤ T < 18°C	-0.022	0.0002	-0.0015
	(0.0148)	(0.0119)	(0.0131)
18°C ≤ T < 21°C	-0.0166	0.0102	0.011
	(0.0162)	(0.0146)	(0.0222)
21°C ≤ T < 24°C	-0.019	0.0031	0.0132
	(0.0186)	(0.0167)	(0.0261)
24°C ≤ T < 27°C	-0.0147	-0.0076	0.0019
	(0.0126)	(0.0177)	(0.0309)
T ≥ 27°C	-0.0124	-0.0283	-0.0243
	(0.0230)	(0.0186)	(0.0322)
Obs	1922000	1922000	1922000
R-squared	0.925	0.925	0.925
Establishment FE	yes	yes	yes
NAICS4-Year FE	yes	yes	yes
Census Division-year FE		yes	
State-year FE			yes
Extreme Weather controls		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 total number of hours worked. The analysis is at the plant-year level and the sample period comprises 1977-2018. The shown coefficients of interest represent the number of days in each respective temperature bin (β_b in Equation (1)) in a given year in a plant's zip code. The number of days 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. All specifications control for average zip code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 5: Short-run effects of temperature on entry and exit

Dep. Var.	Entry				Exit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T < -6°C	-0.0093*	-0.003	-0.0157**	-0.0063	0.0035	-0.0053	0.006	0.0011
	(0.0055)	(0.0076)	(0.0067)	(0.0044)	(0.0034)	(0.0043)	(0.0050)	(0.0044)
-6°C ≤ T < -3°C	-0.0139*	-0.0116	-0.0130*	-0.0055	0.0013	-0.0077	0.0019	-0.0084
	(0.0071)	(0.0060)	(0.0077)	(0.0043)	(0.0037)	(0.0051)	(0.0064)	(0.0073)
-3°C ≤ T < 0°C	-0.0069	-0.0045	-0.0106*	-0.005	0.003	-0.0024	0.0027	-0.0011
	(0.0045)	(0.0062)	(0.0060)	(0.0035)	(0.0033)	(0.0036)	(0.0038)	(0.0037)
0°C ≤ T < 3°C	-0.0029	-0.0025	-0.0063	-0.0048	0.0005	-0.0064**	0.0013	-0.0029
	(0.0035)	(0.0055)	(0.0047)	(0.0030)	(0.0023)	(0.0030)	(0.0032)	(0.0032)
3°C ≤ T < 6°C	-0.0041	-0.0002	-0.0069**	-0.0049*	0.0034	-0.0001	0.0049*	0.0018
	(0.0033)	(0.0051)	(0.0030)	(0.0028)	(0.0021)	(0.0020)	(0.0027)	(0.0022)
6°C ≤ T < 9°C	-0.0006	-0.0006	-0.002	-0.0032	0.0021	-0.0006	0.0007	-0.0008
	(0.0020)	(0.0027)	(0.0020)	(0.0020)	(0.0023)	(0.0024)	(0.0023)	(0.0028)
12°C ≤ T < 15°C	-0.0022	-0.0028	-0.0029*	-0.0043***	-0.0048*	-0.0046	-0.0029*	-0.0029
	(0.0018)	(0.0020)	(0.0016)	(0.0013)	(0.0026)	(0.0032)	(0.0016)	(0.0019)
15°C ≤ T < 18°C	-0.0040*	-0.0059**	-0.0074***	-0.0102***	-0.0027	-0.0017	0.0009	0.0015
	(0.0020)	(0.0025)	(0.0025)	(0.0025)	(0.0021)	(0.0029)	(0.0029)	(0.0029)
18°C ≤ T < 21°C	-0.0073***	-0.0085***	-0.0100***	-0.0123***	-0.0005	-0.0006	0.0024	0.0005
	(0.0019)	(0.0026)	(0.0026)	(0.0022)	(0.0022)	(0.0027)	(0.0026)	(0.0032)
21°C ≤ T < 24°C	-0.0059**	-0.0068**	-0.0091***	-0.0119***	-0.0005	0.0006	0.004	0.0015
	(0.0025)	(0.0032)	(0.0028)	(0.0029)	(0.0021)	(0.0030)	(0.0026)	(0.0024)
24°C ≤ T < 27°C	-0.003	-0.0017	-0.0055*	-0.0074***	0.0015	0.0022	0.0049**	0.003
	(0.0029)	(0.0041)	(0.0031)	(0.0027)	(0.0028)	(0.0042)	(0.0020)	(0.0028)
T ≥ 27°C	-0.0075*	-0.0035	-0.0138***	-0.0083**	0.0045	0.0015	0.0150**	0.0052
	(0.0038)	(0.0046)	(0.0042)	(0.0032)	(0.0043)	(0.0052)	(0.0063)	(0.0039)
Obs	13590000	13590000	13590000	13590000	13590000	13590000	13590000	13590000
R-squared	0.021	0.021	0.189	0.189	0.016	0.016	0.19	0.19
Zipcode FE	yes	yes			yes	yes		
Establishment FE			yes	yes			yes	yes
NAICS4-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Census Division-year FE	yes		yes		yes		yes	
State-year FE		yes		yes		yes		yes
Extreme weather controls	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The table uses the panel data approach described in equation (1) to estimate the short-run effects of temperature on entry (columns (1)-(4)) and exit (columns (5)-(8)). Entry is an indicator variable set equal to one if a plant had zero employees at time t-1 and strictly more than zero employees at time t. 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 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 [9°C,12°C) is used as the reference bin and therefore omitted. All specifications control for average zip code-year precipitation. Zipcode fixed effects are include in columns (1),(2), (5), and (6), while establishment fixed effects are included in columns (3), (4), (7), and (8). 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. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 6: Heterogeneous long-run effects of temperature on number of plants and employment

Dep. Var.	Δ Log(# Estab. of Size < 20)		Δ Log(# Estab. of Size ≥ 20)		Δ Log(Emp. in Estab. of Size < 20)		Δ Log(Emp. in Estab. of Size ≥ 20)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Degree-Days > 18°C / 100	-0.0779**	-0.0528	-0.0213	-0.009	-0.1146***	-0.0833***	0.0739	0.0699
	(0.0385)	(0.0330)	(0.0404)	(0.0391)	(0.0315)	(0.0278)	(0.0616)	(0.0620)
Δ Degree-Days < 18°C / 100	-0.0105	-0.0109	0.0788***	0.0783***	-0.0294	-0.029	0.1070***	0.0938***
	(0.0285)	(0.0263)	(0.0219)	(0.0215)	(0.0295)	(0.0278)	(0.0353)	(0.0348)
Obs	700	700	700	700	700	700	700	700
R-squared	0.146	0.188	0.238	0.257	0.14	0.169	0.241	0.256
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 implications of temperature for number of establishments and establishment employees constructed for establishments with strictly fewer vs. more than 20 employees. In columns 1-4, the left-hand side variable is the change in the natural logarithm of the average yearly number of establishments between the 2010s and the 1980s. In columns 5-8, the left-hand side variable is the change in the natural logarithm of the average yearly number of employees reported by establishments between the 2010s and the 1980s. Throughout, the reported coefficient of interest is the change in the average CDDs (HDDs) between the 2010s and the 1980s at the commuting zone level. Census Division fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the county level are included throughout. Even-numbered columns additionally include county-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornados between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 7: Long-run effects of temperature on number of plants, employment, and 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 / 100	-0.0811*	-0.0654**	0.0362	0.029	0.1208**	0.0976*
	(0.0410)	(0.0321)	(0.0545)	(0.0522)	(0.0554)	(0.0552)
Δ Degree-Days < 18°C / 100	-0.0324	-0.0343	0.0209	0.0055	0.0493**	0.0362
	(0.0416)	(0.0373)	(0.0525)	(0.0477)	(0.0245)	(0.0237)
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 results obtained by estimating the commuting-zone-level long-run specification described in equation (2). In columns (1)-(2), the left-hand side variable is the change in the natural logarithm of the average yearly number of establishments between the 2010s and the 1980s. In columns (3)-(4), the left-hand side variable is change in the natural logarithm of the average yearly number of employees reported by establishments between the 2010s and the 1980s. Throughout, the reported coefficient of interest is the change in the average CDDs (HDDs) between the 2010s and the 1980s at the commuting zone level. Census Division fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the county level are included throughout. Even-numbered columns additionally include county-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 8: Long-run effect 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 / 100	0.0087**	0.0077**	0.0573***	0.0521***
	(0.0036)	(0.0034)	(0.0208)	(0.0184)
Δ Degree-Days < 18°C / 100	0.0046**	0.0036*	0.0152	0.0123
	(0.0020)	(0.0021)	(0.0129)	(0.0127)
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-zon controls		yes		yes

Notes: The table reports results obtained by estimating the commuting-zone-NAICS-3-level long-run specification described in equation (2). In columns (1)-(2), the left-hand side variable is the change in the average yearly fraction of employees reported between the 2010s and the 1980s. 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 2010s and the 1980s, constructed on the basis of the number of employees reported by establishments. Throughout, the reported coefficient of interest is the change in the average CDDs (HDDs) between the 2010s the 1980s at the commuting-zone-NAICS-3 level. Census Division fixed effects, NAICS-3 fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the commuting-zone level are included throughout. Even-numbered columns additionally include commuting-zone-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table 9: Heterogeneous long-run effects of temperature on 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 / 100	-0.0041	0.0036
	(0.0036)	(0.0186)
Δ Degree-Days > 18°C / 100 × 2nd tercile	0.0158**	0.0488*
	(0.0063)	(0.0243)
Δ Degree-Days > 18°C / 100 × 3rd tercile	0.0220***	0.1013**
	(0.0074)	(0.0388)
Panel B: Interacted with tercile indicators of electricity management participation		
Δ Degree-Days > 18°C / 100	0.0135***	0.0907***
	(0.0048)	(0.0294)
Δ Degree-Days > 18°C / 100 × 2nd tercile	-0.0087**	-0.0646**
	(0.0038)	(0.0245)
Δ Degree-Days > 18°C / 100 × 3rd tercile	-0.0096*	-0.0535*
	(0.0048)	(0.0304)
Panel C: Interacted with tercile indicators of # of branches per 1000 people		
Δ Degree-Days > 18°C / 100	0.0094*	0.0611**
	(0.0050)	(0.0236)
Δ Degree-Days > 18°C / 100 × 2nd tercile	-0.0019	-0.0095
	(0.0059)	(0.0333)
Δ Degree-Days > 18°C / 100 × 3rd tercile	-0.0098*	-0.0449
	(0.0057)	(0.0303)
Panel D: Interacted with tercile indicators of frac. of emp. < 20 as multi-unit		
Δ Degree-Days > 18°C / 100	0.0013	0.0435
	(0.0037)	(0.0277)
Δ Degree-Days > 18°C / 100 × 2nd tercile	0.0134	0.0417
	(0.0086)	(0.0380)
Δ Degree-Days > 18°C / 100 × 3rd tercile	0.0075	-0.0079
	(0.0050)	(0.0283)
Observations	11000	11000
Census Division FE	yes	yes
NAICS-3 FE	yes	yes
Commuting zone comtrols	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 implications of temperature on local manufacturing activity. In column (1), the left-hand side variable is the change in the natural logarithm of the fraction of employment in the top 5 largest establishment between the 2010s and the 1980s. In column (2), the left-hand side variable is the change in the natural logarithm of the average yearly Herfindahl-Hirschman Index between the 2010s and the 1980s, constructed on the basis of the number of employees reported by establishments. As of the reported coefficient of interest, in addition to the average CDDs between the 2010s and the 1980s at the commuting zone level, we further investigated its effects with a group of interaction terms. In Panel A, the interaction terms are the indicators for the second and third terciles of electricity prices in 1998, categorized by NACICS-3 industry and census regions. In Panel B, the interaction terms are the indicators for the second and third terciles of electricity management practice participation rates in 1998, categorized by NACICS-3 industry. In Panel C, the interaction terms are the indicators for the second and third terciles of the number of branch per 1000 population in 1994. In Panel D, the interaction terms are the indicators for the second and third terciles of the fraction of establishments with employment less than 20 people being multi-unit in the 1980s (decadal avaerage). Census Division fixed effects, NAICS-3 fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the commuting-zone level are included throughout. All columns further include commuting-zone-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornadoes between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Internet Appendix

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.	
Log(TFP)	Log of total factor productivity.	
Log(Value-Added/Total Hours Worked)	Log of the ratio of value-added to workers' total working hours.	
Log(Total Hours Worked)	Log of workers' total working hours.	
Panel B: LBD Sample		
Entry	An indicator of entry, where employment of the firm in year t-1 is zero and in year t is above zero.	
Exit	An indicator of exit, where employment of the firm in year t is above-zero and in year t+1 is zero.	
Panel C: LBD - Long-run difference between the 1980s and the 2010s		
Δ Degree-Days > 18 ˚C	long-difference in the average degree days above 18 ˚C from 1980s to 2010s.	
Δ Degree-Days < 18 ˚C	long-difference in the average degree days below 18 ˚C from 1980s to 2010s.	
Δ Log(# Establishments)	Long-difference in log of average total establishment from 1980s to 2010s.	
Δ Log(Employment)	Long-difference in log of average total employment from 1980s to 2010s.	
Δ Log(Avg. Size of Establishments)	long-difference in log of average employment size from 1980s to 2010s.	
Δ Frac. of Emp. in Top 5 Largest Estab.	long-difference in the average fraction of employment from top 5 establishments from 1980s to 2010s.	
Δ Log(HHI_Emp.)	long-difference in the average HHI of employment from 1980s to 2010s.	
Δ Log(# Estab. of Size < 20)	long-difference in the log of average number of establishments with < 20 workers from 1980s to 2010s.	
Δ Log(# Estab. of Size $\geq$ 20)	long-difference in the log of average number of establishments with $\geq$ 20 workers from 1980s to 2010s.	
Δ Log(Emp. in Estab. of Size < 20)	long-difference in the log of average employment of establishments with < 20 workers from 1980s to 2010s.	
Δ Log(Emp. in Estab. of Size $\geq$ 20)	long-difference in the log of average employment of establishments with $\geq$ 20 workers from 1980s to 2010s.	
Δ Log(# Estab. of Size < 50)	long-difference in the log of average number of establishments with < 50 workers from 1980s to 2010s.	
Δ Log(# Estab. of Size $\geq$ 50)	long-difference in the log of average number of establishments with $\geq$ 50 workers from 1980s to 2010s.	
Δ Log(Emp. in Estab. of Size < 50)	long-difference in the log of average employment of establishments with < 50 workers from 1980s to 2010s.	
Δ Log(Emp. in Estab. of Size $\geq$ 50)	long-difference in the log of average employment of establishments with $\geq$ 50 workers from 1980s to 2010s.	
Panel D: Control Variables from Other Sources		
Avg. Precipitation	Average daily precipitation of a location-year.	Database built by Wolfram Schlenker
# Events of Floods	Number of drought events in the county-year.	SHEDULS from Arizona State University
# Events of Droughts	Number of drought events in the county-year.	SHEDULS from Arizona State University
# Events of Heatwaves	Number of heatwave events in the county-year.	SHEDULS from Arizona State University
# Events of Hurricane	Number of hurricane events in the county-year.	SHEDULS from Arizona State University
# Events of Tornado	Number of tornado events in the county-year.	SHEDULS from Arizona State University
Δ IPW	Changes in the exposure to the import shock from China from 1990 to 2007.	Autor, Dorn, and Hanson (2013)
Perc. of college students	Percentage of 25-year old or above population finished at least one year of college.	US Census
Log(Population)	Log of county population.	Database built by Andrew Leuven
Log(Income pc)	Log of county per capita income.	IPUSM

Table A.2: Balance Table

Panel A: Commuting zone initial characteristics

	(1)	(2)	(3)	(4)
VARIABLES	perc. of college grads	log(pop.)	log(per cap. income)	ΔIPW_{uit}
Δ Degree-days > 18°C / 100	-0.0261*	0.285	-0.0424	-0.184
	(0.0139)	(0.255)	(0.0292)	(0.580)
Δ Degree-days < 18°C / 100	-0.00651	-0.381***	-0.0268*	-0.530**
	(0.00701)	(0.101)	(0.0143)	(0.238)
Observations	722	722	722	722
R-squared	0.027	0.152	0.025	0.018

Panel B: Long-run changes in the occurrences of natural hazards

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	avg. precipitation	flood	drought	heatwave	hurricane	tornado
Δ Degree-days > 18°C / 100	-0.148***	-1.751	9.718	2.522	1.291	-0.0310
	(0.0371)	(2.683)	(7.633)	(3.271)	(2.018)	(2.131)
Δ Degree-days < 18°C / 100	-0.00382	1.058	5.256	2.477	0.134	-1.046
	(0.0199)	(1.203)	(3.249)	(1.513)	(0.466)	(0.687)
Observations	722	722	722	722	722	722
R-squared	0.112	0.012	0.015	0.009	0.011	0.026

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

Table A.3: Short-run effects of temperature on productivity: Robustness to alternative measure of productivity that excludes energy costs

Dep. Var.	$\log(\frac{\text{value added excluding energy costs}}{\text{total working hours}})$		
	(1)	(2)	(3)
T < -6°C	0.0114	0.0145	0.042
	(0.0173)	(0.0272)	(0.0489)
-6°C ≤ T < -3°C	-0.0223	-0.0069	0.0157
	(0.0215)	(0.0314)	(0.0475)
-3°C ≤ T < 0°C	-0.0038	-0.0079	0.0028
	(0.0201)	(0.0245)	(0.0392)
0°C ≤ T < 3°C	0.0034	0.0064	0.005
	(0.0131)	(0.0172)	(0.0299)
3°C ≤ T < 6°C	0.0031	0.0183	0.0144
	(0.0156)	(0.0201)	(0.0258)
6°C ≤ T < 9°C	-0.006	0.0115	0.0099
	(0.0123)	(0.0123)	(0.0146)
12°C ≤ T < 15°C	0.0028	-0.0009	-0.0017
	(0.0126)	(0.0131)	(0.0152)
15°C ≤ T < 18°C	-0.0098	-0.0259*	-0.0431**
	(0.0118)	(0.0136)	(0.0161)
18°C ≤ T < 21°C	0.001	-0.0209	-0.041
	(0.0124)	(0.0227)	(0.0300)
21°C ≤ T < 24°C	-0.0254*	-0.0539***	-0.0793***
	(0.0132)	(0.0130)	(0.0159)
24°C ≤ T < 27°C	-0.0202	-0.0405***	-0.0630***
	(0.0129)	(0.0141)	(0.0159)
T ≥ 27°C	-0.0006	-0.0275*	-0.0660***
	(0.0118)	(0.0146)	(0.0221)
Obs	1922000	1922000	1922000
R-squared	0.787	0.788	0.789
Establishment FE	yes	yes	yes
NAICS4-Year FE	yes	yes	yes
Census Division-year FE		yes	
State-year FE			yes
Extreme weather controls		yes	yes

Notes: We use the panel data approach described in equation (1) to estimate the short-run effect of temperature on the natural log of value added excluding energy costs divided by total working hours of workers. The analysis is at the plant-year level and the sample period is 1977 to 2018. The shown coefficients of interest represent the number of days in each respective temperature bin (β_b in equation (1)) in a given year in a plant's ZIP Code. The number of days 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. All specifications control for average ZIP Code-year precipitation and include establishment fixed effects. Further fixed effects are included as indicated. Extreme weather controls include number of hurricanes and number of tornadoes, both of which are measured at the county-year level. Regressions are estimated using ASM sample weights. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

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

Dep. Var.	Energy Costs/TVS		log(TFP)	
	(1)	(2)	(3)	(4)
T < -6°C	0.0009	0.0002	0.0027	-0.0162
	(0.0014)	(0.0021)	(0.0225)	(0.0361)
-6°C ≤ T < -3°C	0.0001	-0.0019	-0.0093	-0.0012
	(0.0016)	(0.0026)	(0.0218)	(0.0317)
-3°C ≤ T < 0°C	0.0000	-0.001	-0.0368*	-0.0439
	(0.0011)	(0.0016)	(0.0204)	(0.0309)
0°C ≤ T < 3°C	0.0011	-0.0001	-0.0246	-0.0259
	(0.0009)	(0.0014)	(0.0203)	(0.0222)
3°C ≤ T < 6°C	0.0009	0.0004	-0.0256*	-0.0304**
	(0.0010)	(0.0014)	(0.0137)	(0.0139)
6°C ≤ T < 9°C	0.0001	0.0003	-0.0042	-0.0069
	(0.0010)	(0.0010)	(0.0123)	(0.0146)
12°C ≤ T < 15°C	0.0007	0.0006	-0.0152	-0.0124
	(0.0010)	(0.0012)	(0.0108)	(0.0105)
15°C ≤ T < 18°C	0.0001	0.0005	-0.0303*	-0.0487***
	(0.0009)	(0.0014)	(0.0162)	(0.0132)
18°C ≤ T < 21°C	0.0018***	0.0024**	-0.0385**	-0.0614***
	(0.0006)	(0.0009)	(0.0181)	(0.0217)
21°C ≤ T < 24°C	0.0023***	0.0035***	-0.0543***	-0.0809***
	(0.0007)	(0.0011)	(0.0141)	(0.0180)
24°C ≤ T < 27°C	0.0024***	0.0042***	-0.0523***	-0.0844***
	(0.0007)	(0.0015)	(0.0165)	(0.0250)
T ≥ 27°C	0.001	0.0028	-0.0452**	-0.0685**
	(0.0010)	(0.0021)	(0.0198)	(0.0323)
Obs	975000	975000	975000	975000
R-squared	0.826	0.827	0.793	0.794
Establishment FE	yes	yes	yes	yes
NAICS4-Year FE	yes	yes	yes	yes
Census Division-year FE	yes		yes	
State-year FE		yes		yes

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

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

Dep. Var.	Energy Costs/TVS		log(TFP)	
	(1)	(2)	(3)	(4)
T < -6°C	0.0009	0.0016	0.0285*	0.0463
	(0.0009)	(0.0016)	(0.0166)	(0.0295)
-6°C ≤ T < -3°C	0.0007	0.0003	-0.0043	0.0173
	(0.0010)	(0.0019)	(0.0208)	(0.0319)
-3°C ≤ T < 0°C	-0.0001	0.0000	0.0042	0.0143
	(0.0007)	(0.0011)	(0.0176)	(0.0236)
0°C ≤ T < 3°C	0.001	0.001	-0.0013	-0.0075
	(0.0006)	(0.0009)	(0.0121)	(0.0149)
3°C ≤ T < 6°C	0.0007	0.0001	0.0034	0.0057
	(0.0006)	(0.0007)	(0.0102)	(0.0105)
6°C ≤ T < 9°C	0.0008	0.0006	-0.0006	0.0071
	(0.0007)	(0.0009)	(0.0097)	(0.0148)
12°C ≤ T < 15°C	0.0009	0.0001	-0.006	-0.0012
	(0.0006)	(0.0007)	(0.0097)	(0.0097)
15°C ≤ T < 18°C	0.0011*	0.0008	-0.0097	-0.0234**
	(0.0007)	(0.0009)	(0.0082)	(0.0094)
18°C ≤ T < 21°C	0.0016***	0.0018**	-0.0144	-0.0314
	(0.0006)	(0.0008)	(0.0137)	(0.0201)
21°C ≤ T < 24°C	0.0021***	0.0024***	-0.0305***	-0.0501**
	(0.0006)	(0.0008)	(0.0109)	(0.0189)
24°C ≤ T < 27°C	0.0020***	0.0028***	-0.0317***	-0.0546***
	(0.0005)	(0.0009)	(0.0105)	(0.0187)
T ≥ 27°C	0.0019***	0.0027**	-0.0144	-0.0324
	(0.0007)	(0.0013)	(0.0128)	(0.0216)
Obs	1715000	1715000	1715000	1715000
R-squared	0.796	0.797	0.769	0.77
Establishment FE	yes	yes	yes	yes
NAICS4-Year FE	yes	yes	yes	yes
Census Division-year FE	yes		yes	
State-year FE		yes		yes

Notes: In this table, we replicate the results presented in Tables 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: Heterogeneous long-run effects of temperature on number of plants and employment

Dep. Var.	Δ Log(# Estab. of Size < 50)		Δ Log(# Estab. of Size $\geq$ 50)		Δ Log(Emp. in Estab. of Size < 50)		Δ Log(Emp. in Estab. of Size $\geq$ 50)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Degree-Days > 18 °C / 100	-0.0786**	-0.0504	-0.0256	-0.052	-0.1056***	-0.0704*	0.0446	0.0521
	(0.0364)	(0.0352)	(0.0494)	(0.0385)	(0.0369)	(0.0379)	(0.0590)	(0.0573)
Δ Degree-Days < 18 °C / 100	0.0192	0.0209	0.1054***	0.1006***	0.0227	0.027	0.1234***	0.1063***
	(0.0225)	(0.0209)	(0.0307)	(0.0280)	(0.0188)	(0.0182)	(0.0379)	(0.0353)
Obs	700	700	700	700	700	700	700	700
R-squared	0.146	0.188	0.238	0.257	0.14	0.169	0.241	0.256
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 implications of temperature for number of establishments and establishment employees constructed for establishments with strictly fewer versus more than 20 employees. In columns 1-4, the left-hand side variable is the change in the natural logarithm of the average yearly number of establishments between the 2010s and the 1980s. In columns 5-8, the left-hand side variable is the change in the natural logarithm of the average yearly number of employees reported by establishments between the 2010s and the 1980s. Throughout, the reported coefficient of interest is the change in the average CDDs (HDDs) between the 2010s and the 1980s at the commuting zone level. Division fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the commuting zone level are included throughout. Even-numbered columns additionally include commuting zone-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornados between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.

Table A.7: Long-run effect of temperature on wages and labor productivity

Dep. Var.	Δ Log(Payroll / Emp.)		Δ Log(Value Added over Total Working Hours)	
	(1)	(2)	(3)	(4)
Δ Degree-Days > 18 °C / 100	0.0416***	0.0422***	0.0436***	0.0403**
	(0.0147)	(0.0145)	(0.0151)	(0.0168)
Δ Degree-Days < 18 °C / 100	0.0192*	0.0178*	0.0081	0.0089
	(0.0104)	(0.0096)	(0.0099)	(0.0107)
Obs	11000	11000	6900	6900
R-squared	0.07	0.073	0.054	0.054
Census Division FE	yes	yes	yes	yes
NAICS-3 FE	yes	yes	yes	yes
Commuting zone controls		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 implications of temperature on local manufacturing activity. In columns (1)-(2), the left-hand side variable is the change in the natural logarithm of the average payroll over the number of employees between the 2010s and the 1980s. In columns (3)-(4), the left-hand side variable is the change in the natural logarithm of the average value added over employees' total working hours between the 2010s and the 1980s. Throughout, the reported coefficient of interest is the change in the average CDDs (HDDs) between the 2010s and the 1980s at the commuting zone level. State fixed effects and a control for the change in average precipitation between the 2010s and the 1980s at the commuting zone level are included throughout. Even-numbered columns additionally include commuting-zone-level controls for preconditions (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 (Autor et al. 2013), and changes in occurrences of hurricanes and tornados between the 2010s and the 1980s. Standard errors are reported in parentheses and clustered at the state level. Significance is indicated at 1% (***), 5% (**), and 10% (*) level.