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ABSTRACT

We use plant-level data from the US Census of Manufacturers to study the short and long run effects of temperature on manufacturing activity. We document that temperature shocks significantly increase energy costs and lower the productivity of small manufacturing plants, while large plants are mostly unaffected. In US counties that experienced higher increases in average temperatures between the 1980s and the 2010s, these heterogeneous effects have led to higher concentration of manufacturing activity within large plants, and a reallocation of labor from small to large manufacturing establishments. We offer a preliminary discussion of potential mechanisms explaining why large manufacturing firms might be better equipped for long-run adaptation to climate change, including their ability to hedge across locations, easier access to finance, and higher managerial skills.

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I Introduction

Average temperatures in the continental United States have increased substantially over the past century (IPCC, 2021). The pace of warming has accelerated starting in the 1980s, with a median increase in temperature across US counties of 0.6°C, and nine in ten counties experiencing an increase in their average temperatures between the 1980s decade and the 2010s decade. Understanding the impact of a warming climate on economic activity has gained the center of the political and academic debate.[1]

We contribute to this debate by providing new evidence on the impact of temperature variation on U.S. manufacturing activity using four decades of plant-level data from the U.S. Census Bureau. Three features of the Census data are particularly relevant. First, the availability of detailed establishment-level characteristics, such as energy costs and productivity, allows a comprehensive anatomy of the impact of temperature shocks. Second, the ability to observe the cross-section of plants allows us to study the heterogeneous effects of temperature shocks on establishments of different sizes. Third, observing plant performance over four decades enables us to study the response of manufacturing activity to long-run temperature changes. To the extent that plants differ in their sensitivity to temperature variation, one may expect manufacturing activity to concentrate among those firms that are better able to adapt. Indeed, the main contribution of this paper is to document the impact of temperature variation on local industry concentration, and to discuss its potential drivers.

Our empirical strategy builds on two approaches to estimate the effect of temperature on manufacturing plants. The first approach aims at capturing the contemporaneous response of manufacturing outcomes to short-term (yearly) temperature shocks. The second approach aims at capturing the long-term response of manufacturing activity to changes in the average climate experienced by a county in the last four decades. To measure manufacturing outcomes, we use two datasets. We combine the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM) to measure plants' energy costs, productivity, and size. We use the Longitudinal Business Database (LBD), an administrative register that tracks all business establishments, to identify plant entry and exit in different geographic locations.

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 think of each US ZIP code or county as a small open economy and manufacturing as a tradable sector

[1] 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)).

whose demand is geographically sparse across the US 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, input costs associated with temperature management – mainly expenditures in electricity and fuel – and productivity react to contemporaneous temperature shocks. In particular, warmer than usual temperatures increase energy spending 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 hotter than usual temperatures dissuade entry. Indeed, it is plausible that key industrial decisions such as scaling back on 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 in following years. On the other hand, the cumulative effect of several years of warmer than usual weather might push managers to respond on the intensive and extensive 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 county, we use a long differences approach as in Burke and Emerick (2016). In particular, we estimate a county-level regression relating long-run changes in manufacturing activity to long-run changes in average temperatures between the 1980s decade and the 2010s decade, controlling for state-specific common trends and for differential trends across counties with different initial observable characteristics. We find that, over the last four decades, areas that 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. While the number of large plants did not increase, the point estimates on employment indicate that large plants were able to absorb at least part of the labor force lost by smaller manufacturing establishments. This indicates a faster reallocation of employment from small to large plants in counties that experienced a higher increase in temperature in the last four decades.

Then, we investigate the impact of higher average temperatures on different measures of industrial concentration at the county level. We find that counties that in the 2010s decade had a standard deviation higher increase in temperature – about 100 degree days per year above 18°C – relative to the 1980s decade, experienced a 1.4 percentage points larger increase in the share of employment concentrated in the top 5 largest plants, and a

5.1 percent larger increase in the Herfindahl-Hirschman concentration index. Overall, the results indicate that faster warming in the last four decades has led to higher concentration of industrial activity among larger plants.

The finding that faster warming has led to higher concentration of manufacturing activity among larger firms suggests that such firms might be better equipped for long-run adaptation to climate change. We conclude the paper by discussing several potential mechanisms that can rationalize this result. First, large firms might 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). Second, large firms might also have better access to external finance, which allows them to cope with weather shocks, reducing the need to downscale employment or close plants. Large firms might have better trained managers who can both understand the change in firm exposure to climate risk and invest in adaptation. Finally, if higher temperature leads to out-migration, large firms – which tend to be more productive and pay higher wages on average – might be less exposed to increases in local wages due to a decline in local labor supply.

Related Literature

Climate economists have provided ample evidence on 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). Of particular interest to us is the work on country-level output and productivity. That work generally documents adverse effects of climate change in developing economies and explains the general lack of effects in developed countries by adaptation (Burke et al. (2015), Chen and Yang (2019), Colacito et al. (2019), Dell et al. (2009), Dell et al. (2012), Gallup et al. (1999), Hsiang (2010), Jones and Olken (2010)).[2] Within this area of inquiry, we study the impact of temperature shocks and long-run warming on establishments in the U.S. manufacturing sector.

Though in developed economies a higher capacity of adaptation may be presumed the norm, in manufacturing not all facilities are climate-controlled, the production process itself produces substantial heat, and the power grid providing energy to industrial establishments is subject to stress when temperatures rise above certain thresholds (Graff Zivin and Neidell, 2014). Moreover, heterogeneity in establishment size and organizational structure may affect establishments' ability to respond to as well as their incentives to prepare for temperature shocks (Castro-Vincenzi 2022, Zivin and Kahn 2016, Somanathan et al.

[2] A notable exception exists in the agricultural sector where short-term temperature shocks are generally found to 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 US, Lobell et al. (2011) for global evidence, Gupta et al. (2017) and Auffhammer et al. (2006) for evidence on India).

2021). Consistent with the idea that firms are heterogeneous with respect to their ability to absorb temperature shocks and adapt to climate change, we find temperature shocks and climate change to have adverse average effects on U.S. manufacturing firms. These effects are almost entirely concentrated among small firms, and they have implications for local industry concentration.

More specifically, our findings relate to three strands of the literature. First, in documenting the adverse effects of climate change on U.S. manufacturing establishments, we contribute to the rapidly growing body of empirical work on climate and firms. Among others, higher temperatures have been documented to reduce sales among non-U.S. global firms (Pankratz et al. (2023); using the 1995-2019 period), affect the profitability of public firms across more than 40 percent of U.S. industries (Addoum et al. (2021); 1990-2015), and reduce total factor productivity for Chinese manufacturing firms (Zhang et al. (2018); 1998-2007).

Existing work has also documented that suppliers of the same client lose two percent in sales when faced with a one degree Celsius temperature increase vis-a-vis other same-client suppliers; clients dynamically adjust their supplier network (Custodio et al. (2022), Pankratz and Schiller (2021); both using the 2000-2015 period). Contrary to the by-and-large adverse effects on firms documented in these papers, Addoum et al. (2020) find no effects of higher temperatures on establishment sales and productivity of establishments owned by public U.S. firms, which are likely larger plants.[3] In order to speak to this apparent ambiguity in findings, we study the effects of temperature changes on a representative sample of U.S. manufacturing establishments, including small- and medium-sized establishments, over four decades. We focus on entry and exit as possible margins of adjustments, and, by including small establishments, are able to highlight that small firms bear the costs of a warming climate. Contrary to existing work on firms, our sample period covers over four decades (1977-2018), and is hence not dominated by the so-called hiatus, a 16-year period (1998-2013) of slow average warming (Cahill et al. (2015), Hsiang and Kopp (2018)). Length of the sample period and granularity of the data allow us to include multiple high-order fixed effects all the while considering non-linearities along the full spectrum of the temperature distribution.

Second, our results further speak directly to 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)). With this, we think our findings are informative also for the literature on adaptation, i.e., the speed of adjustment to changes in the environment. While Samuelson (1947) and Viner (1958) provide theoretical guidance, empirical evidence has been mixed and setting-dependent. In agriculture, for

[3] Other related work has used different climate shocks, such as floods, to document effects on entry, employment, and output, see, e.g., Desmet and Rossi-Hansberg (2021), Lin et al. (2021), and Jia et al. (2022).

instance, Burke and Emerick (2016) find long-run adaptation to offset less than half and possibly none of the short-term losses inflicted by increasing temperatures on corn yields. Similarly, Hornbeck (2012) finds effects of soil erosion during the 1930s to have effects on productivity even two decades later, though Olmstead and Rhode (2011) find some evidence of adaptation in wheat cultivation to harsher environments.[4] One means of adaptation that has received considerable attention in climate studies and constitutes a likely force behind our results is the availability of air conditioning (AC). Somanathan et al. (2021) show that climate control mitigates some of the productivity losses caused by heat but also point out that in some industries, such as the garment industry, adaptation of AC may not be justified given that the additional electricity costs more than offset value-added. This point–that more productive firms have greater incentives to adapt–is formalized in Zivin and Kahn (2016) and exploited to show that the overall impact of heat on industry productivity is dampened: productive firms have a higher output share and are more likely to adopt AC. Adaptation to floods, in the meantime, is front-and-center in Castro-Vincenzi (2023) where large car manufacturers reallocate production away from affected plants. By-and-large, our evidence on small firms and the mediating role played by energy costs corroborates these findings. More broadly, while the adverse effects of climate change on firms are for the most part found among developing economies (Dell et al. (2012), Burke et al. (2015)), we show that they matter in U.S. manufacturing, and especially to small firms.

Third, our findings are linked closely to the literature on industry concentration, a literature that documents increasing trends in industry concentration for the U.S. over recent decades (e.g., De Loecker et al. (2020), Grullon et al. (2019)). Drivers behind this increased industry concentration 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)). To this debate, we add climate change as a driver which, through its adverse impact on small firms, contributes to increased local industry concentration.

The rest of the paper is organized as follows. Section II describes the data and offers some background information on changes in average temperatures experienced in the continental U.S. in recent decades. Section III presents the identification strategy. Section IV discusses the short-run and long-run effects of temperature changes on manufacturing activity, and offers some preliminary discussion of mechanisms that can rationalize our findings.

[4] To illustrate the range of settings to which theories of adaptation have been applied, Davis and Weinstein (2002) and Miguel and Roland (2006) show temporary negative shocks to have no adverse long-lasting effects on economic and quantitative demographic outcomes in a very different setting, that of the bombings of Japan and Vietnam.

II Data and Background

II.A Data

Data on establishment activity, climate, and economic and demographic controls are from various sources.

Manufacturing establishments data. 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. LBD provides information on establishment geographic locations and industry classification. We further exploit data on the number of employees to distinguish by establishment size. We have access to the LBD data for the time period of 1977-2019.

Second, we combine the Census of Manufacturing Firms (CMF) and the Annual Survey of Manufacturers (ASM) for details on activities of manufacturing establishments, which are classified using 2-digit NAICS code 31-33. CMF provides for all US manufacturing plants with at least one employee for the Census years only (every five years). ASM provides data for non-CMF years for a sample of 50,000-70,000 manufacturing establishments, including all establishments with more than 250 employees and a sample of smaller establishments. Sampling weight is included for all plant-years to reflect that smaller plants are less likely to be surveyed relative to their large peers.[5] We keep ASM plants during census years from the CMF. Our ASM/CMF data span the time period of 1973-2018. From these two data sets, we use detailed industry classification, identification of business group affiliation, output (measured by value of shipments), energy costs, total working hours, and employment. We also use total factor productivity (TFP) as in Foster et al. (2016) (see their Appendix). Data quality is ensured through a mandatory reporting requirement and fines for misreporting.

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 United States over the 1950-2019 period is provided by the PRISM Climate Group. To suit our purpose, we rely on the cleaned version provided on Wolfram Schlenkers homepage.[6] Data includes daily minimum and maximum temperatures for 2.5 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

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

[6]See http://www.columbia.edu/ ws2162/links.html for details such as treatment of missing values and selection of underlying stations.

observations (see Auffhammer et al. (2013) for a discussion of these and other potential pitfalls).

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 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 zipcode centroid and their inverse distance to the centroid as the weight, a method that follows Heutel et al. (2021). For our county-level analysis, we weight all grid-level temperature observations within a county by their inverse distance to the geographic county midpoint. We obtain precipitation information using the same method. On the basis of the resulting respective zip code-day and county-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 (CDD) and Heating Degree Days (HDD).

We further obtain data on extreme weather events such as droughts and floods, heatwaves and winter weather, as well as hurricanes and tornadoes from SHELDUS.[7] SHELDUS covers the 1960-2021 period and assigns events to counties; underlying data is 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 . We use hazards reported by SHELDUS as controls and also to validate our temperature data.

Economic and demographic controls. Three county-level economic and demographic controls are based on the 1980 Census and serve as controls for pre-sample period conditions. Income per capita and population are obtained directly from the Census webpage, and 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). A further 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.

II.B Background on changes in temperature in the US

The contiguous U.S. has experienced substantial increases in average temperature over the last century. According to the climatology literature described in the IPCC (2021) report, the significant emergence of changes in temperature relative to historical averages

[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, AZ: Arizona State University. Available from https://cemhs.asu.edu/sheldus

occurred in North America after 1981.[8] Figure I puts this observation into historical context by showing the dynamics of annual average surface temperature anomalies across the contiguous 48 states over the last 120 years. A temperature anomaly is the difference between the average annual temperature and the average temperature over the 1901-2000 period. Figure I 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 temperature increased rapidly and consistently after 1980.[9] This trend is particularly pronounced in the 2000s and 2010s, and the 2012 to 2016 period experienced some of the highest abnormal temperatures.

This recent trend of increasing temperatures is predicted to continue for the next decades, as confirmed by long-run projections of U.S. temperatures for the remainder of the 21st century. In Figure II we utilize the "big data" generated by Hsiang et al. (2017) to illustrate predicted long-run trends. These data contain binned projections of daily weather (1981-2100) for US counties using 44 different climate models, and records the number of days that fall within 1-Celsius degree bins within a year (from -20°C to 40°C).[10] Next, we take the average days across all climate models for each county-year, and then calculate the mean value across all counties in a decade.

Climate modeling generally considers four Representative Concentration Pathways (RCPs) to describe different 21st-century pathways of greenhouse gas (GHG) emissions and atmospheric concentrations. The RCPs include a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high GHG emissions (RCP8.5, frequently referred to as "business as usual" or "worst case scenario"). The most pronounced pattern in Figure II 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 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 worse-case scenario.

Figure III illustrates the geographic distribution 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 across the US, with the largest increases in

[8] See IPCC (2021), page 133. Historical climate is calculated using temperature data for the baseline period 1850-1900.

[9] To further illustrate the recent increase in average temperatures, our own analysis shows that over the last four decades, the median increase in average temperature across counties was 0.6°C, an increase in average temperature was observed in more than 90% of all counties, and the average county experienced 3.4 more days per year above 26°C (and 2 fewer days per year below -6°C).

[10] In order to align the arguments in this section with our later analysis, we group temperature projections into coarser bins of 3 Celsius degrees. 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.

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

III Empirical Strategy

Our empirical strategy builds on two approaches to estimate the effect of temperature on manufacturing outcomes. The first approach aims at capturing the contemporaneous response of manufacturing outcomes to short-term (yearly) temperature shocks. The second approach aims at capturing the long-term response of manufacturing activity to changes in the average climate experienced by a county in the last four decades.[11]

III.A Panel approach to study the effects of temperature shocks

We start by studying the effect of year-to-year changes in 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 indexes manufacturing plants, j indexes industries, $z(s)$ indexes the ZIP code z in state s where the plant is located, and t indexes years. Our plant-year panel spans the time period of 1977-2018. 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 impacts as it allows arbitrary non-linear relationships between temperature and outcome variables.[12] We divide the temperature distribution in 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. We exclude the median temperature bin 9°C-11°C in all specifications, so that the estimated β_b coefficients should be interpreted as the effect of an additional day with 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 state-level in all specifications.

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

[11] See, e.g., Auffhammer (2018), Burke and Emerick (2016), and Blanc and Schlenker (2017) for a comprehensive discussion of each method, as well as their advantages and challenges.

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

include in equation (1) 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. We include 4-digit NAICS industry fixed effects interacted with year fixed effects to absorb any aggregate trends at industry-level experienced by US manufacturing plants. In addition, when examining outcome variables obtained from ASM/CMF (i.e., energy costs, productivity, and employment), regressions are estimated using ASM sample weights.

Notice that temperature shocks can affect local manufacturing activity in two ways. First, they can affect the input costs and the production processes of plants, for example by increasing energy consumption, increasing maintenance costs of machinery and equipment or affecting the productivity of workers. We think of this set of forces as manufacturing *supply* shocks. Additionally, temperature shocks can affect local demand from consumers, for example via their impact on the profitability of local agriculture (Burke and Emerick, 2016). In the context of US manufacturing studied in this paper, we think of each US ZIP code or county as a small open economy and manufacturing as a tradable sector whose demand is geographically sparse across the US 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.

Temperature shocks might be associated with extreme weather events, and thus affect manufacturing outcomes via this association. We explore this relationship in Figure IV, which reports the effect of an additional day with average temperature within each bin on average precipitation and the incidence of extreme weather events recorded in the aforementioned SHELDUS database. Perhaps unsurprisingly, additional hot days are associated with lower average precipitation and lower probability of floods. Additional hot days are mechanically associated with a higher probability of droughts and heatwaves, which are themselves defined based on prolonged occurrence of high temperature days. The effect of temperatures on tornados and hurricanes are small and mostly insignificant. 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 tornados.

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

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

$$\Delta y_{c(s),2010s-1980s} = \alpha_s + \beta_1 \Delta CDD_{c(s),2010s-1980s} + \beta_2 \Delta HDD_{c(s),2010s-1980s} + \lambda X_{c(s)} + u_{c(s)} \quad (2)$$

To estimate equation (2), we construct decadal averages of yearly data for both the manufacturing outcome variables and the temperature variables in the 1980-1989 decade and in the 2010-2019 decade in each county c. Long run differences are then calculated 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 changes in temperature relative to historical averages occurred after 1981. Second, prior literature studying economic adaptation to long-run changes in temperature has also focused on the post-1980 period, noting that warming trends in the US after the 1980s have been larger than those observed in earlier periods (Burke and Emerick, 2016). Third, as explained in section II.A, the US Census LBD data provides consistent coverage of manufacturing activity for the period 1980-2019. Thus, we think of the forty year period 1980-2019 as long enough to capture significant changes in the average climate of each location.

In equation (2), we use two parsimonious measures of temperature: cooling degree days (CDD) and heating degree days (HDD). These are standard measures meant to capture the energy required to keep temperature at a baseline level, and have the advantage of capturing 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 – the baseline temperature at which no heating or cooling is necessary – conditional on the average daily temperature being above 18°C.[13] For each county, we compute CDD as the sum of all $CDDs$ over a year. $HDDs$ are defined in the same way for days with 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 counties. The inclusion of state fixed effects removes any role of unobservable state-level trends. However, a potential concern is whether their inclusion also removes most of the relevant variation in long-term changes in climate. We investigate this concern in Figure V, where we plot 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,

[13] 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`.

between the 1980s and the 2010s, most US counties experienced an increase in average yearly cooling degree days, or degree days above 18°C, while the changes in heating degree days were mostly negative in the same period. This is consistent with a significant warming trend across US counties during the last four decades. Panel (b) reports the distribution of long run changes in decadal averages of HDD and CDD in deviation from state averages. As shown, even net of state trends, there is still significant variation in degree days across counties. For example, a standard deviation in the raw distribution of long run changes in CDD corresponds to 120 degree days (see Table I), while after removing state fixed effects a standard deviation in the same variable corresponds to 57 degree days. We rely on this variation in our estimates of long-run effects of changes in average climate on manufacturing activity.

The key identifying assumption in equation (2) is that differential changes in degree days observed over the last four decades in each county are uncorrelated with other local trends that might also affect the outcomes of interest. State fixed effects reduce the role of unobservables by removing state-level aggregate trends. Still, a potential concern is that long run changes in temperature might be correlated with unobservable county-level trends. In support of empirical approaches similar to the one described in equation (2), previous literature in environmental economics has underlined how "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). In support of this assumption, in Panel A of Table A.2 we show that long-run changes in average temperatures are not strongly correlated with county-level initial characteristics, including population, per capita income, and share 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 US manufacturing in the period under study, such as import competition from China (Autor et al., 2013), finding no significant correlation (column (4)).

In Panel B of Table A.2 we 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, we find non-significant correlations in the expected direction between changes in temperatures and changes in the frequency of natural disasters. The correlation with average precipitation is instead negative and strongly significant. In the empirical analysis we include in equation (2) the initial county characteristics reported in Panel A 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 Empirical Results

IV.A Short-run response to temperature shocks

In this section we study 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 usually experienced in a given location: energy costs and productivity of manufacturing plants. Next, we study the impact of temperature shocks on both the intensive margin (plant size) and the extensive margin (entry and exit) of manufacturing activity.

Energy costs. Higher than usual temperatures can increase energy costs of manufacturing production in several ways. First, due to an increase in the demand for electricity necessary to cool down work environments via air conditioning, as well as to cool down machinery and equipment used in production. Second, higher temperatures can negatively affect the efficiency of energy production systems and transmission: an increase in hot days implies that power plants need to be cooled down more often or cannot operate due to decreases in water availability, and electrons move slower inside transmission lines at higher temperatures (Bartos et al., 2016).[14]

We estimate equation (1) when the outcome variable is energy costs at the plant level. The results are reported in Table II and visualized in Figure VII. Energy costs are defined as the monetary value of expenses in electricity and fuel divided by the value of shipments at plant level. All coefficients are multiplied 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 average temperature above 18°C experience statistically significant increases in energy costs. The effect is monotonically increasing in temperature bins and the magnitude of the coefficients implies that a year with 100 additional days in the temperature bins above 18°C would generate a 0.2 percentage points increase in energy costs as a share of value of shipment. This corresponds to about 9% of the sample average in the outcome variable. On the other hand, we find mostly non significant effects of additional cold days on energy consumption, with the exception of the coldest temperature bin.

Next, we investigate the effect of temperature shocks on energy costs of small vs large plants in Figure VIII. Throughout the paper, we define small vs large plants based on number of employees. Results are similar depending on whether we consider as small plants those with less than 20 or 50 employees. Panels (a) and (b) of Figure VIII

[14] Although the effect of temperature on energy production systems is relevant in the aggregate, it does not necessarily manifest in the same ZIP code of the manufacturing plant using the energy (because power plants might be located elsewhere), and thus it is less likely to be captured by our empirical strategy.

document that the effects of temperature shocks on energy costs are concentrated among small plants. Large manufacturing plants – and especially those above 50 employees – seem to be largely immune from the effects of temperature shocks on energy costs. A potential explanation of this finding is that large plants might be operating with capital – machinery, equipment, buildings – of higher "quality" and that is less sensible to temperature shocks. For example, larger plants might have better insulated buildings or newer machinery and equipment used in production that are more energy efficient and less prone to overheating, thus requiring less cooling of production spaces.

Productivity. A large existing literature has documented a negative relationship between temperature and labor productivity (see, among others, Graff Zivin and Neidell (2014), Heal and Park (2013), Hsiang (2010), and Somanathan et al. (2021)). Rising temperatures can affect manufacturing productivity via their effect on both the performance of workers and the productivity of machinery and equipment. The effect of temperature on workers' productivity can arise due to fatigue and lower ability to focus, as well as absenteeism. Stricter safety standards have increased the amount of protective gear necessary in manufacturing workplaces over time, amplifying the exhaustion of performing the same task at a higher temperature. Another amplifying effect might arise from the faster physical pace or longer shifts set by manufacturing plants in order to meet production goals and remain competitive in a global market. On the other hand, direct evidence on the effects of temperature on the performance of machinery and equipment is more sparse, though Zhang et al. (2018) show suggestive evidence that higher temperatures lower capital productivity for Chinese manufacturers. In what follows we document similar negative effects of temperature shocks on productivity for US manufacturing plants, and provide new evidence on how these effects differ for small vs large plants.

The results of estimating equation (1) when the outcome variables are different measures of productivity are reported in Table III and visualized in Figure IX. 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 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 by a given plant-location. We find a negative and monotonic effect of temperature 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 year with 100 additional days in the temperature bins above 18°C would generate a 4 percentage points decline in TFP and a 7 percentage point decline in labor productivity as measured by value added per hour worked.[15]

Next, in Figure X, we report the results when splitting the sample between small vs 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 manufacturing plants are small and mostly non statistically significant. Mechanisms that can rationalize 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 tend to produce with physical capital whose performance is less affected by abnormal temperatures. Examples include higher probability to have temperature control systems (Zivin and Kahn, 2016), or better insulated work environments. Differences in the type of labor force employed in large vs small plants might also play a role. For examples, large plants are matched with more productive, more motivated workers whose performance is less affected by temperature shocks.

Size, Entry and Exit. After documenting contemporaneous effects of temperature shocks on energy costs and productivity, we now focus on studying whether US 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 total number of employee-hours. The results are reported in Table IV and visualized in Figure XI. As shown, we find no contemporaneous response to additional hot days relative to what usually experienced by a given plant, and a positive but noisy response to additional cold days. Figure XII also documents 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 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

[15] 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 alternative measures of productivity that are not a function of energy costs, such as: value of shipments per worker or per hour worked, and value added per worker or per hour worked where value added is constructed without including energy among inputs. We find similar results using these alternative measures, which indicates that the effect of temperature shocks on productivity is not mechanically driven by the effect of temperature shocks on energy costs.

has positive employment in the LBD in year t but no recorded employment in year $t+1$. This is because plants that are in operation 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 V and visualized in Figure XIII. We find that entry is more likely to occur in years with additional "median" temperature days, while the probability of entry declines with both additional cold and hot days. As shown, higher than usual number of hot days are detrimental for the opening of a new plant in a given location, though 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 plant opening in that year. This is an economically large effect when considering the average entry rate in our sample is 0.07 (Table I).

Figure XIV 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 – in part because most manufacturing plants are small at the time of opening.

The results for exit are reported in columns (5) to (8) of Table V and visualized in Figure XV. We find mostly small in magnitude and non significant effects of temperature shocks on exit. The probability of exit monotonically increases with temperature bins above 18°C but even estimates on highest temperature realizations are not statistically significant. Notice 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 XVI, and show a similar pattern as Figure XV.

Discussion of short-run response to temperature shocks. There are two key findings that emerge from our estimates of the short run effects of temperature shocks on manufacturing outcomes. First, input costs associated with temperature management (such as energy costs) and productivity react to contemporaneous temperature shocks. In particular, higher than usual temperatures increase energy spending and decrease plant productivity. However, in the short run, plants do not seem to respond to temperature shocks via contemporaneously adjusting employment in a significant way. We also do not find evidence that these temperature shocks significantly affect the probability of exit, while hotter than usual temperatures seem to dissuade entry. Second, the effects described above are driven by small manufacturing plants, while we document mostly small and non significant effects for large establishments.

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 scaling back on 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 in following years. 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 county we estimate equation (2) described in section III.B. This equation relates long-run changes in manufacturing activity with long-run changes in average temperatures between the 1980s decade and the 2010s decade. As discussed in section II.B, the US has experienced a large increase in average temperatures between the 1980s and 2010s, with substantial variation even across counties within the same state. Because the short-run effects indicate that there are significant heterogeneous effects of temperature shocks across plants of different size, in what follows we investigate the effects of long run changes in average temperatures separately for small vs large plants.

Number of plants and employment. We start by studying the effect of long-run changes in temperature on long-run changes in the number of plants of different size in a given county. The results are reported in columns (1) to (4) of Table VI, panels A and B. The point estimate reported in column (2) of Panel A implies that counties that in the 2010s decade had a standard deviation higher increase in temperature – about 100 degree days per year above 18°C – relative to the 1980s decade experienced a 4.2 percent larger decline in the number of manufacturing plants with less than 20 employees. This effect remains stable in magnitude and statistically significant when controlling for the set of initial county characteristics described in section III.B, which lends support to the empirical strategy.

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 documented 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. We also document that changes in cooling degree days between the 1980s and the 2010s had smaller and non statistically significant effects on the number of manufacturing plants in a given county. In Panel B, we replicate the analysis using 50 employees as a threshold to define large plants, finding similar results.

Next, we investigate the long-run effects of higher average temperatures on number of workers employed by small vs large plants. The results are reported in columns (5) to (8) of Table VI. 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 counties that in the 2010s decade had a standard deviation higher increase in temperature – about 100 degree days per year above 18°C – relative to the 1980s decade experienced a 5.9 percent larger decline in the number of workers employed by manufacturing plants with less than 20 employees. The effects on number of workers in large plants are positive, indicating that while the number of large plants does not increase, these plants are able to absorb the labor force lost by smaller manufacturing establishments.

Finally, in Table VII we document the overall effect of long-run increases in temperatures on total number of plants, overall employment and average plant size in a given county. We find negative but noisy estimates on the effects on total number of plants, and positive but non significant effects on total employment. Columns (5) and (6) show instead positive and significant effects on average plant size. Overall, these results indicate that that counties with faster warming temperatures did not experience significant major changes in total employment, but mostly a reallocation of production from small to large plants, leading to a 7.7 percent higher increase in average plant size for a standard deviation higher increase in average temperatures over the last four decades.

Concentration of manufacturing activity. The results presented in Tables VI and VII 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. In particular, we focus on the percent of employment concentrated in the top-5 largest plants in a given county, and the Herfindahl-Hirschman Index (HHI). We compute the Herfindahl-Hirschman Index as the sum of squared values of the employment shares of each plant in a given county. The index thus captures the amount of concentration in the employment share across plants, with higher values indicating higher concentration.

The results are reported in Table VIII. The point estimates indicate positive and significant effects of long run changes in average temperatures on industrial concentration. In particular, we find that counties that in the 2010s decade had a standard deviation higher increase in temperature – about 100 degree days per year above 18°C – relative to the 1980s decade experienced a 1.4 percentage points larger increase in the share of employment concentrated in the top 5 largest plants, and a 5.1 percent larger increase in the Herfindahl-Hirschman concentration index. Overall, the results indicate that faster warming in the last four decades has led to higher concentration of industrial activity among larger plants. We discuss potential mechanisms behind this result in the next section.

IV.C Preliminary discussion of mechanisms

The finding that faster warming has led to higher concentration of manufacturing activity among larger plants suggests that such plants might be better equipped for long-run adaptation to climate change. In this preliminary version of this section we list potential economic mechanisms that can rationalize the main results of the paper. We plan to test these mechanisms empirically in the next iteration of the paper.

i. Hedging. 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 large firms in the car industry are able to partly absorb weather shocks – like floods – by reallocating production from affected plants to non-affected plants. This hedging strategy requires firms to keep spare capacity in each location, which multi-plant large firms are more likely to be able to afford.

ii. Access to finance. 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. Easier access to external finance also facilitates investments in long term projects necessary to make their production process less sensitive to climate change.

iii. Managerial skills. Large firms might have better trained managers who can both understand the change in firm exposure to climate risk and invest in adaptation. Examples of such investments include the adoption of technologies that reduce the effect of temperature on labor productivity, such as automated warehouse management systems, or the update of buildings and machinery so that they can better withstand higher temperatures or natural disasters.

iv. Migration. Over the long run, counties that experienced higher increases in temperatures might also have experienced larger out-migration. Local decline in labor supply would increase local wages, which tend to negatively affect small firms the most, as they tend to be less productive and pay lower wages.

V Concluding remarks

In this paper, we study the short-run and long-run implications of temperature variation on U.S. manufacturing establishments. We find extreme temperatures, and particularly warmer temperatures, to result in short-term increases in the cost of inputs associated with temperature management (electricity and fuel costs), short-term declines in productivity, and short-term deterrence of entry. While these effects are concentrated in small manufacturing plants, large establishments are mostly unaffected. In the long run, we find that areas faced with greater increases in average temperatures between the 1980s and the 2010s experienced larger declines in the number of small plants. While the number of large plants did not increase, large plants were able to absorb at least part of the labor force lost by smaller manufacturing establishments.

Taken together, large firms are better equipped for long-run adaptation to climate change, which results in greater industry concentration. Among the various channels that may help large plants adapt better are (i) their ability to hedge in order to absorb weather shocks, (ii) better access to external finance, (iii) higher managerial quality, and (iv) lower sensitivity to local wage increases. Our results highlight that recent increases in industry concentration are note solely due to technological and political factors, but that climate change plays an important role as well.

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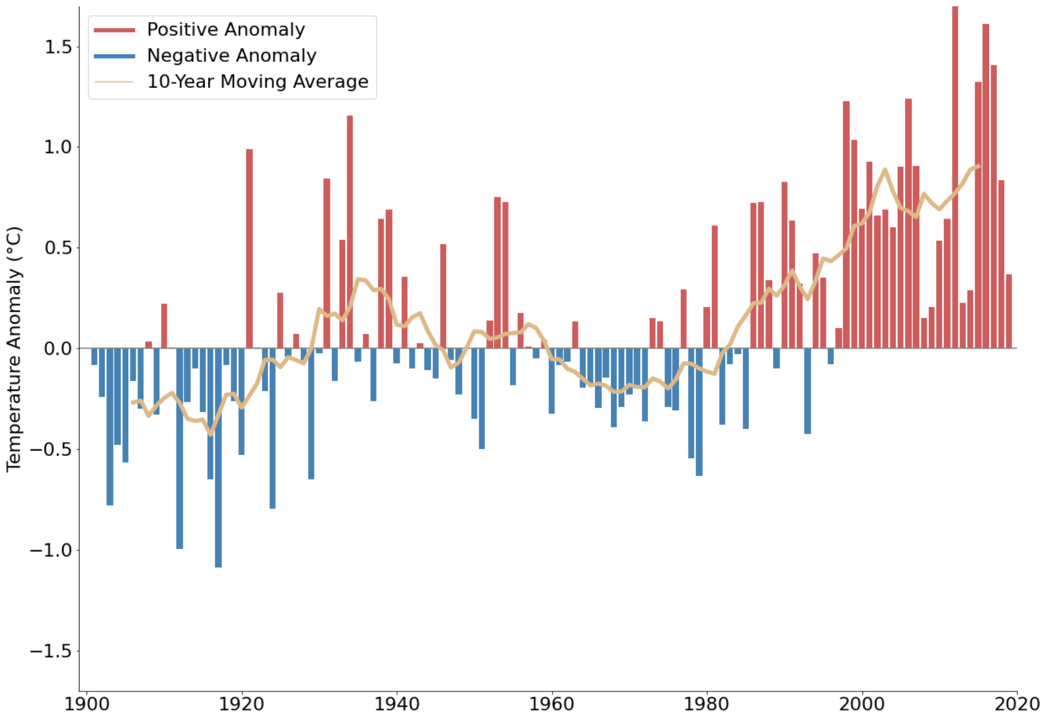
VI Figures

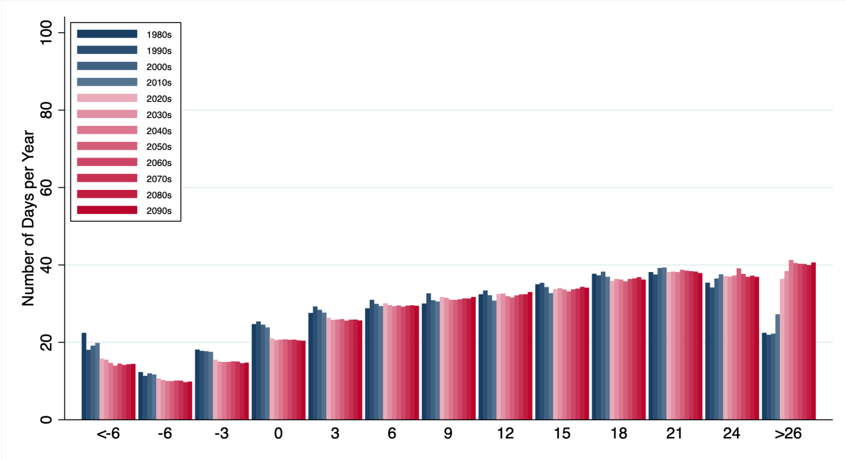
Figure I: Temperature Trend in the U.S.



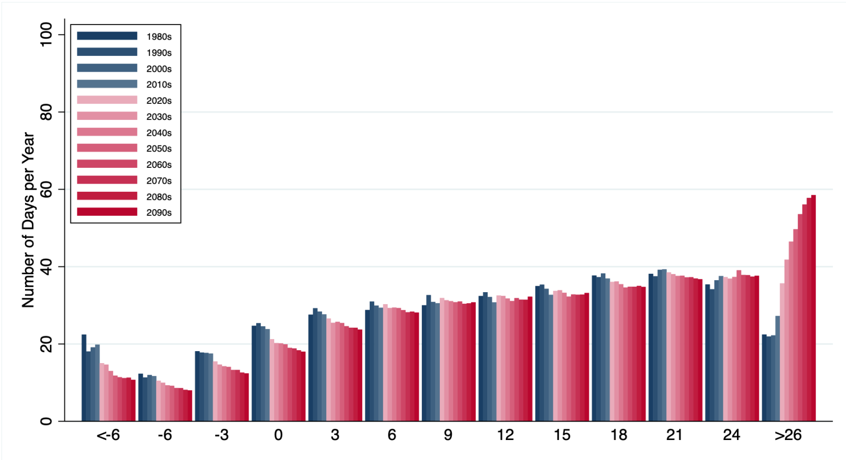
Note: Data source: National Oceanic and Atmospheric Administration (NOAA).
The figure illustrates the temperature dynamics for the contiguous 48 U.S. states from 1901-2019. The anomaly is calculated as the difference between the annual temperature and the average temperature between 1901-2000. The yellow line represents the 10-year moving average of the anomalies.

Figure II: Distribution of temperature days by bin over time

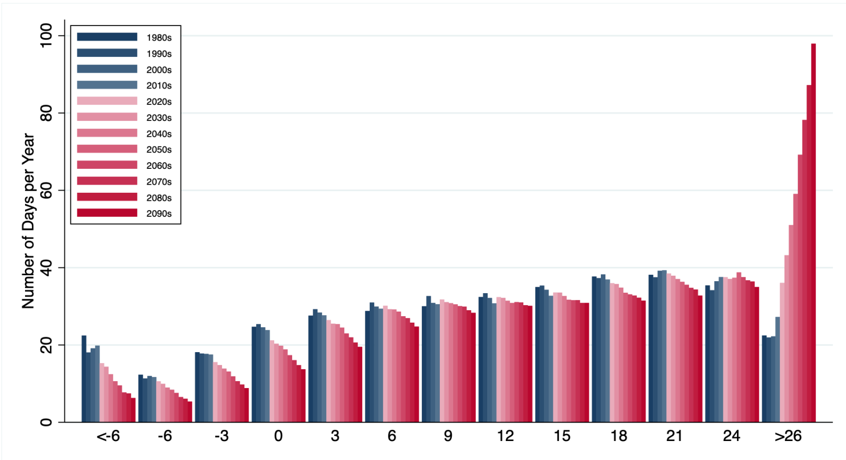
(a) RCP 2.6



(b) RCP 4.5



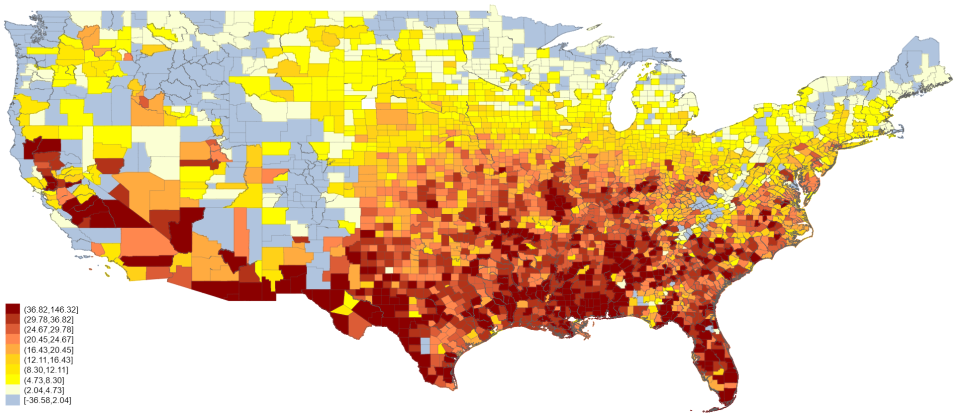
(c) RCP 8.5



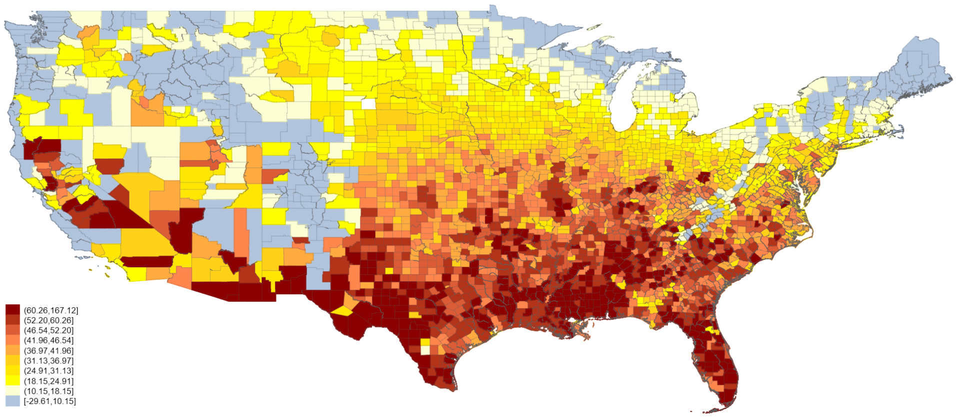
Note: Data source: Hsiang et al. (2017).
This figure presents the U.S. long-run temperature projection in the 21st century. Temperature projection is calculated as the average across 44 climate models. We first group temperature projection into 3-Celsius degree bins, and then calculate the average number of days that fall under each degree bin across all U.S. counties for each decade. We include three different RCPs in this figure, including a stringent mitigation scenario in panel (a) (RCP2.6), an intermediate scenarios in panel (b) (RCP4.5), and one scenario with very high GHG emissions in panel (c) (RCP8.5, frequently referred to as “business as usual” or “worst case scenario”).

Figure III: Projected changes in the number of days above 26C between the 1980s and the 2090s

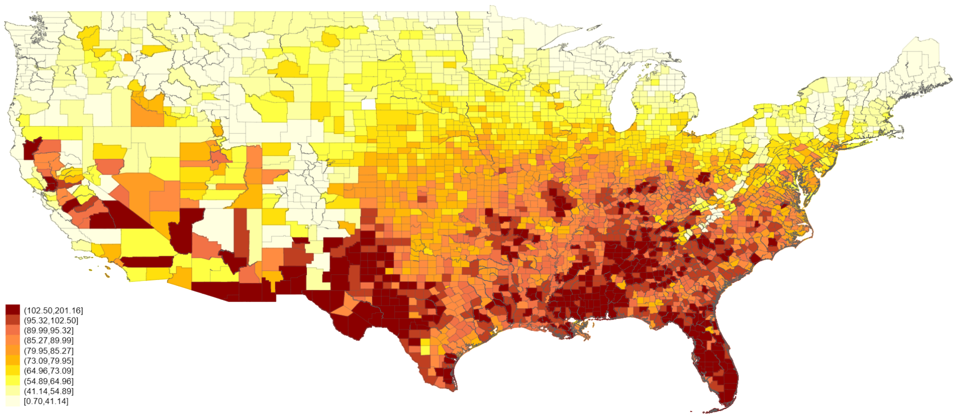
(a) RCP26



(b) RCP45



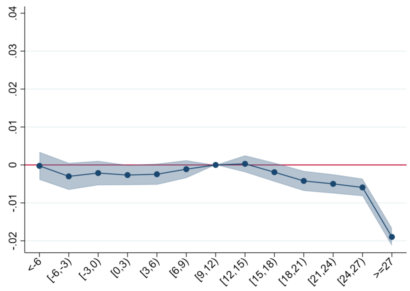
(c) RCP85



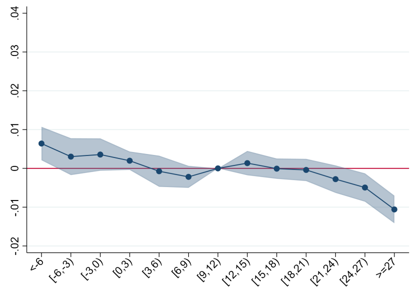
Note: Data source: Hsiang et al. (2017).
This figure presents the geographic distribution of projected changes in the number of days above 26°C between the 1980s and the 2090s. For each county-year, the number of days above 26°C is calculated as the average across 44 different climate models. We include three different RCPs in this figure, including a stringent mitigation scenario in panel (a) (RCP2.6), an intermediate scenarios in panel (b) (RCP4.5), and one scenario with very high GHG emissions in panel (c) (RCP8.5, frequently referred to as “business as usual” or “worst case scenario”)

Figure IV: Temperature bins and probability of extreme weather events

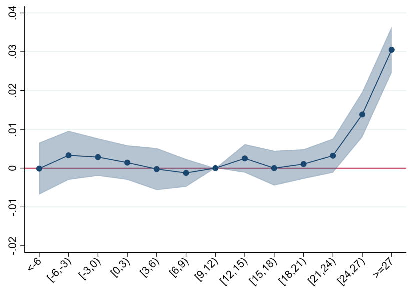
(a) Average Precipitation



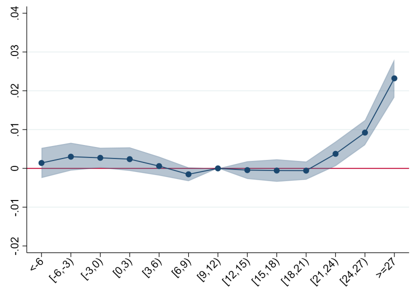
(b) Number of Floods



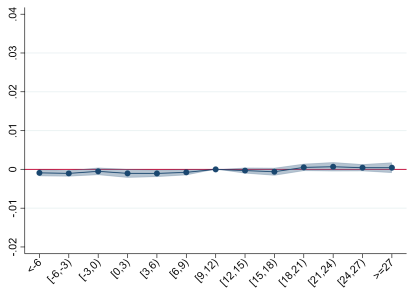
(c) Number of Droughts



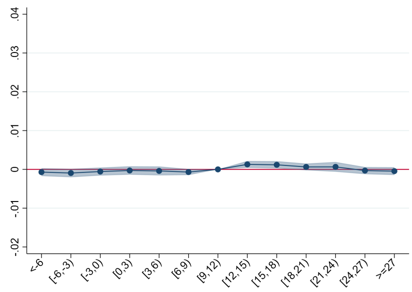
(d) Number of Heatwaves



(e) Number of Hurricane



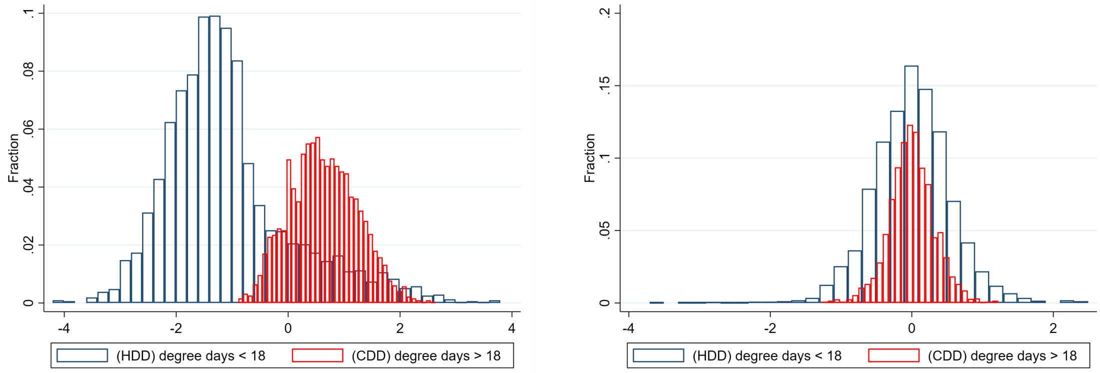
(f) Number of Tornado



Note: Data source: Schlenker Columbia and SHELDUS. The figures show the year-to-year county-level correlation between the 3-degree temperature bins and the average precipitation and the number of a set of natural disaster events. County and year fixed effects are included in all regressions, and the standard errors are clustered at the state level.

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

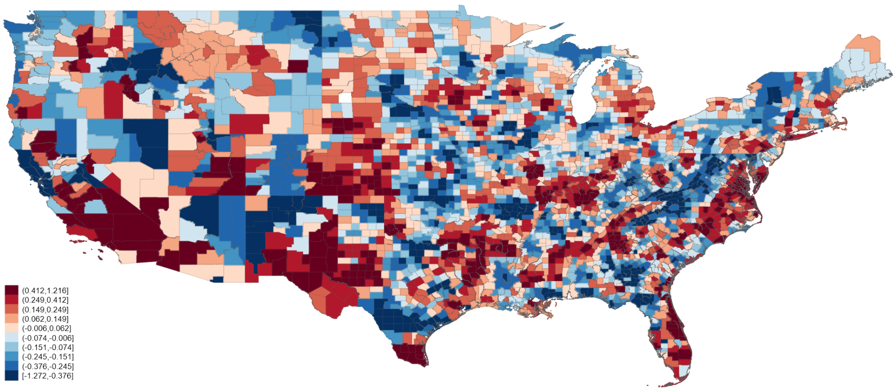
(a) Raw changes (b) Residual changes after removing state FE



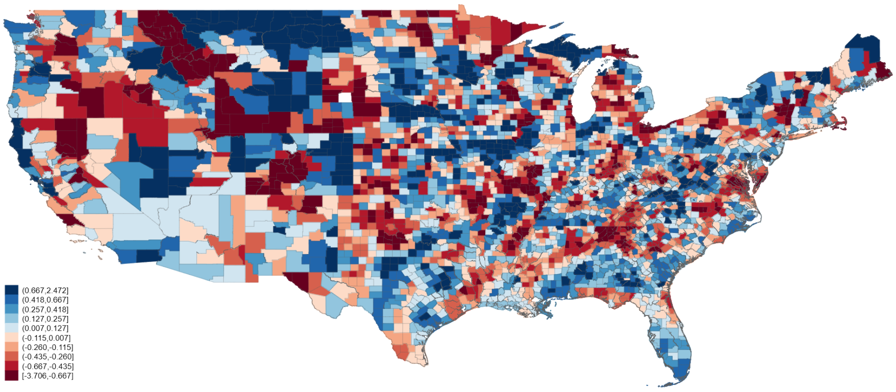
Note: Data source: Schlenker Columbia. The blue bins plot the long run difference in heating degree days (HDD) between the 1980s and the 2010s, and the red bins plot that for the cooling degree days (CDD). One unit in the x-axis corresponds to 100 degree-days. The CDD is defined as the difference in degrees between the average daily temperature in a location and 18°C, conditional on the average daily temperature being above 18°C. The HDD is defined in the same way for days with average daily temperature below 18°C.

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

(a) Δ (degree days $>$ 18°C)

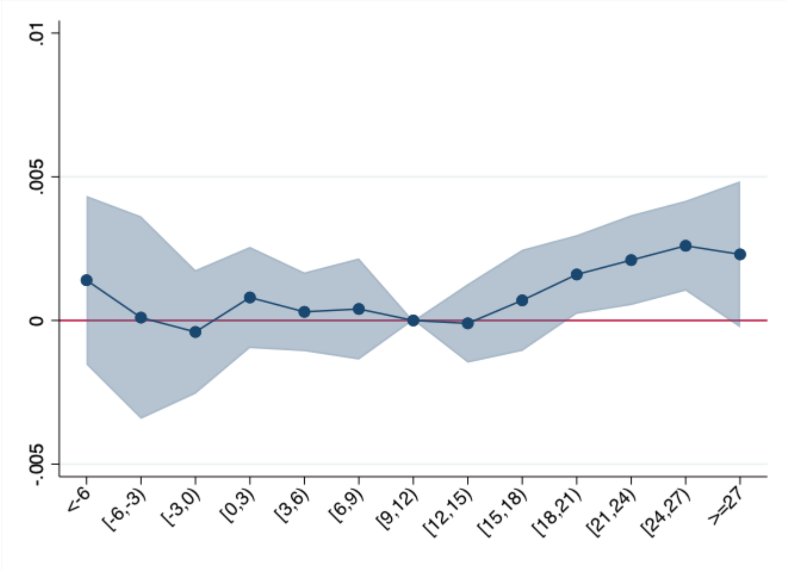


(b) Δ (degree days $<$ 18°C)



Red indicates counties that have become warmer between the 1980s and 2010s relative to state-level long run trend. Similarly, blue indicates counties that have become cooler between the 1980s and 2010s relative to state-level long run trend.

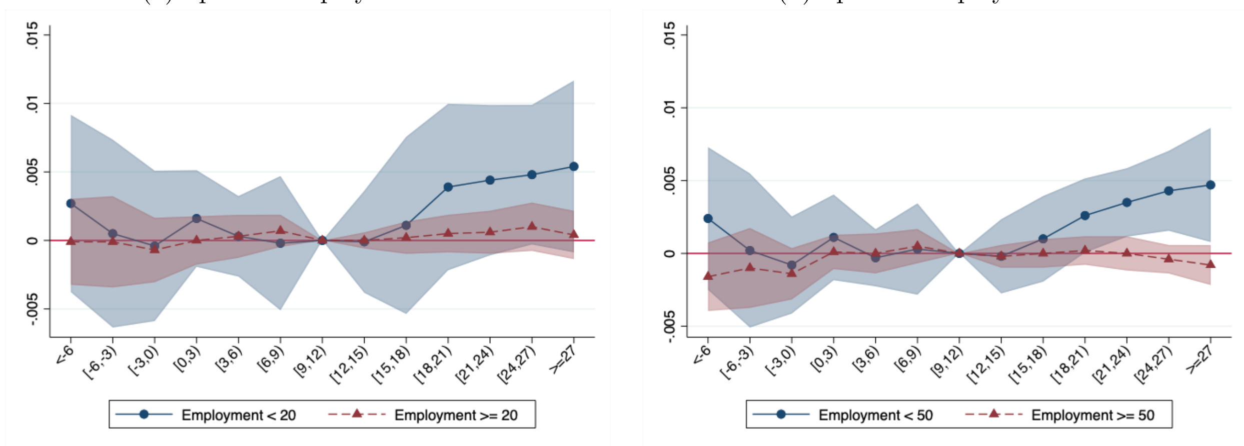
Figure VII: Effect of year-to-year temperature changes on energy costs



Note: The figure shows the point estimates and the 95% confidence interval of β_b in Equation (1), with the outcome variable being the share of energy costs to total value of shipments. The temperature bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

Figure VIII: Heterogeneous effect of year-to-year temperature changes on energy costs

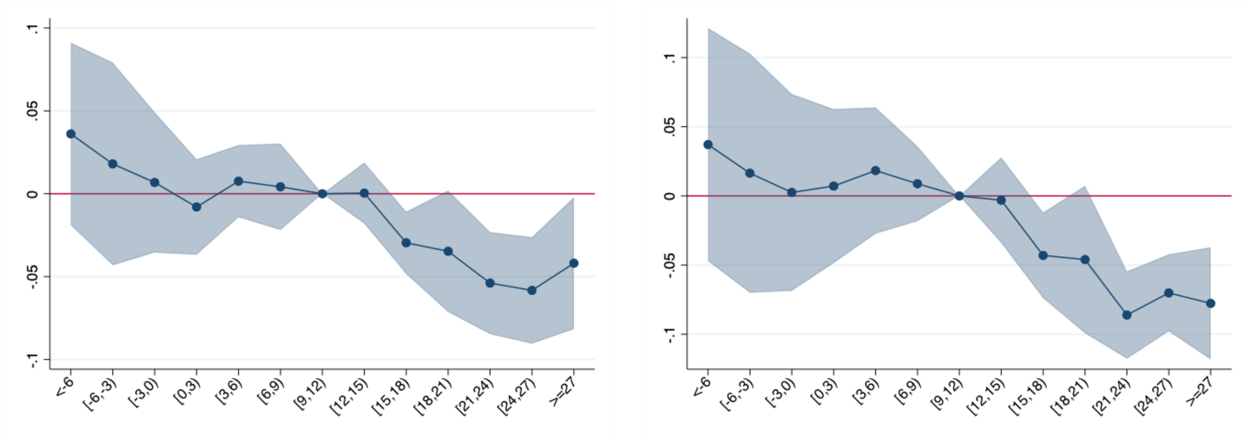
(a) Split at Employment=20 (b) Split at Employment=50



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different subsamples. Figure (a) divides the sample to plants with an employment size of more than 20 and below 20. Figure (b) divides the sample to plants with an employment size of more than 50 and below 50. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

Figure IX: Effect of year-to-year temperature changes on Productivity

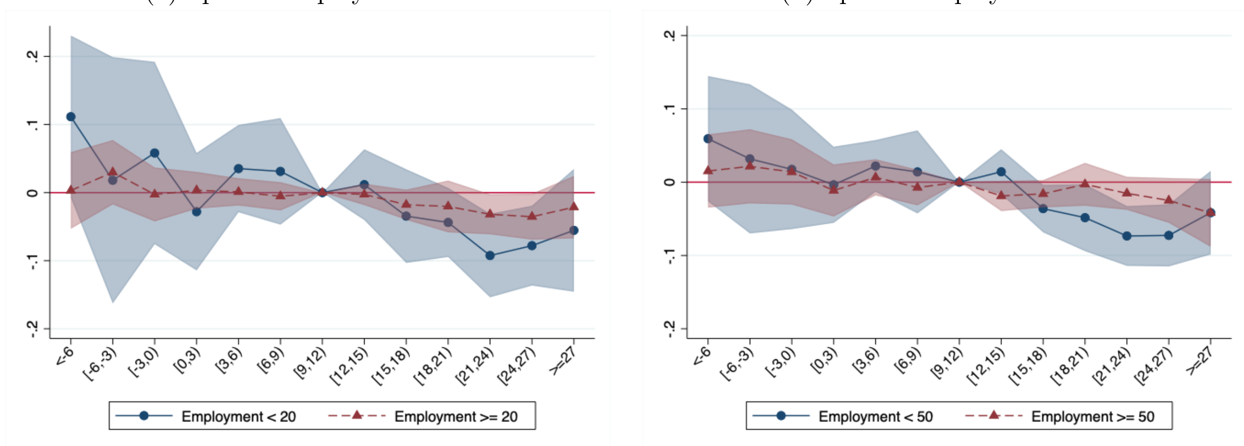
(a) Log(TFP) (b) Log(Value Added/Total Working Hours)



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different measurement of productivity. Figure (a) uses log-transformed TFP as the outcome variable, while Figure (b) uses log-transformed division of value added by total employee hours. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

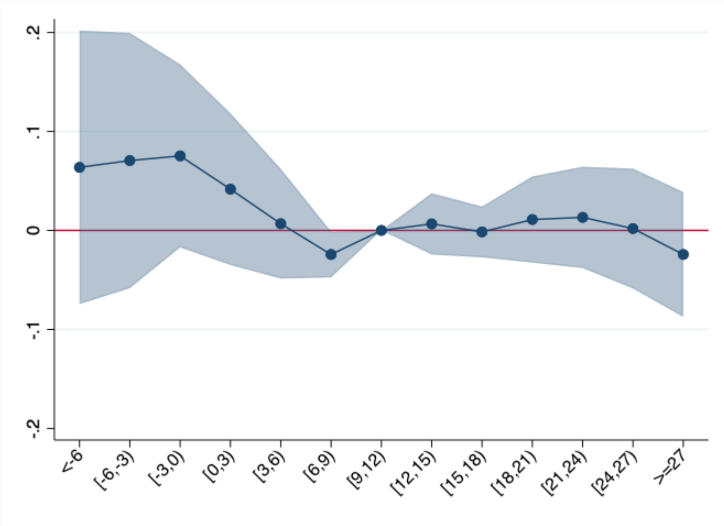
Figure X: Heterogeneous effect of year-to-year temperature changes on Log(TFP)

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



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different subsamples. The outcome variable is log(TFP). Figure (a) split the sample by whether the employment is above or below 20, and Figure (b) split the sample by the employment size threshold of 50. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

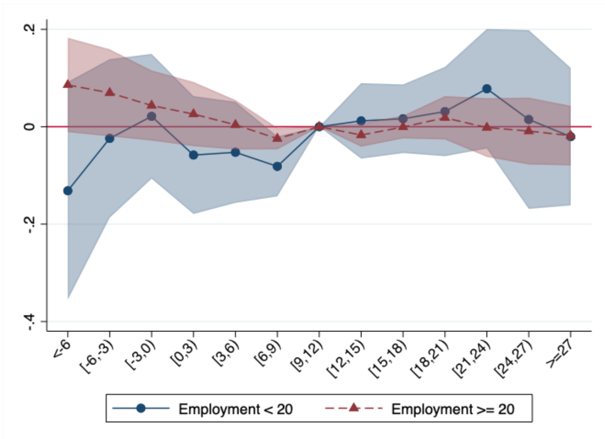
Figure XI: Effect of year-to-year temperature changes on total employee-hours



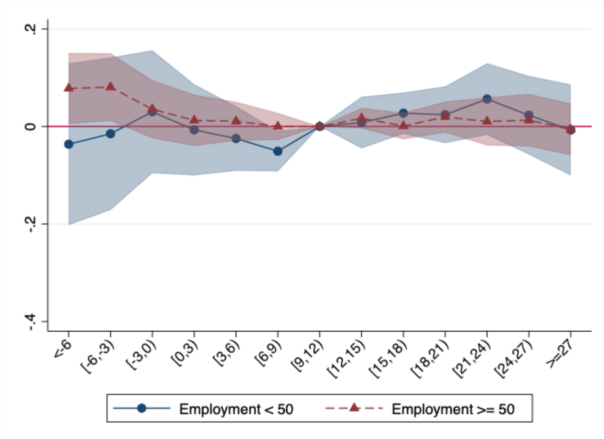
Note: The figure shows the point estimates and the 95% confidence interval of β_b in Equation (1), with the outcome variable being the total employee hours. The temperature bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

Figure XII: Heterogeneous effects of year-to-year temperature changes on total employee-hours

(a) Employment < 20

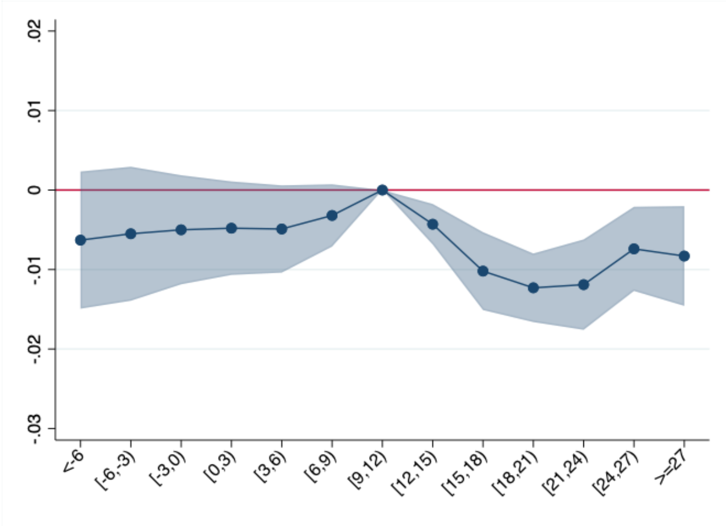


(b) Employment < 50



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different subsamples. The outcome variable is total employee hours. Figure (a) split the sample by whether the employment is above or below 20, and Figure (b) split the sample by the employment size threshold of 50. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Regressions are estimated using ASM sample weights. Standard errors are clustered at the state level.

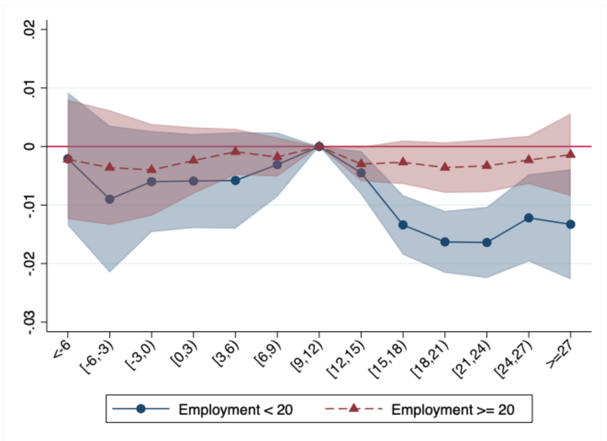
Figure XIII: Effect of year-to-year temperature changes on entry



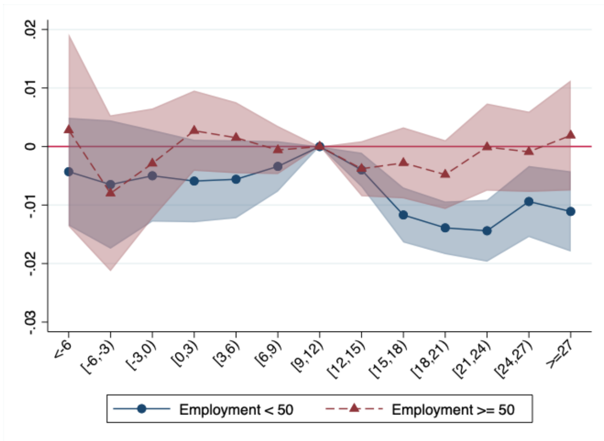
Note: The figure shows the point estimates and the 95% confidence interval of β_b in Equation (1), with the outcome variable being the probility of entry (%). We define entry of a plant i in ZIP code z during year t as a dummy equal to 1 if plant i if plant i has no employment in year $t-1$ and positive employment in year t. The temperature bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Standard errors are clustered at the state level.

Figure XIV: Heterogeneous effects of year-to-year temperature changes on entry

(a) Split at employment=20

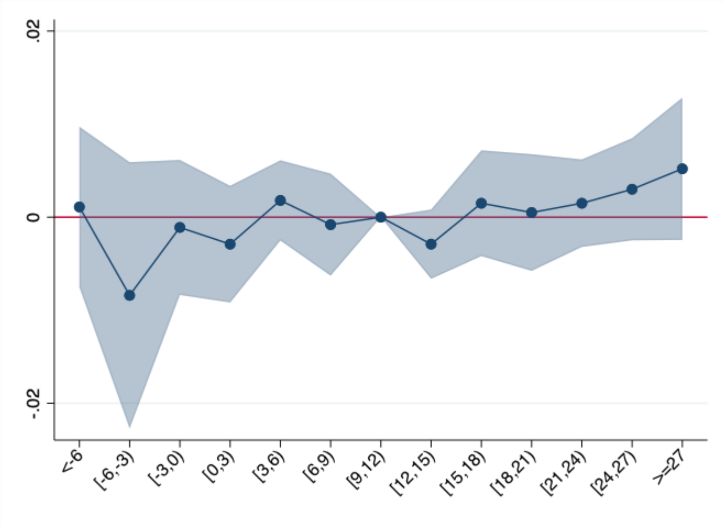


(b) Split at employment=50



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different subsamples. The outcome variable is the probability of entry (%). Figure (a) split the sample by whether the employment is above or below 20, and Figure (b) split the sample by the employment size threshold of 50. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Standard errors are clustered at the state level.

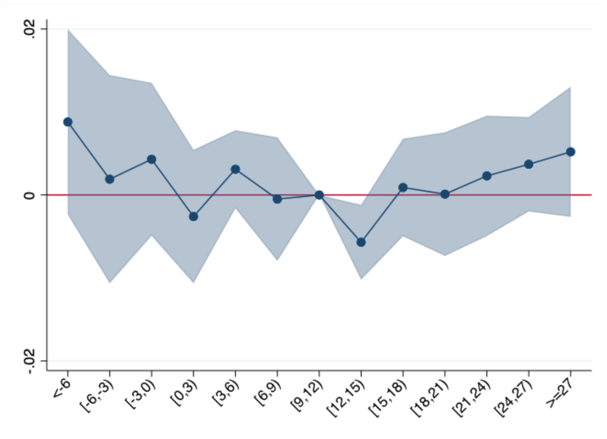
Figure XV: Effect of year-to-year temperature changes on exit



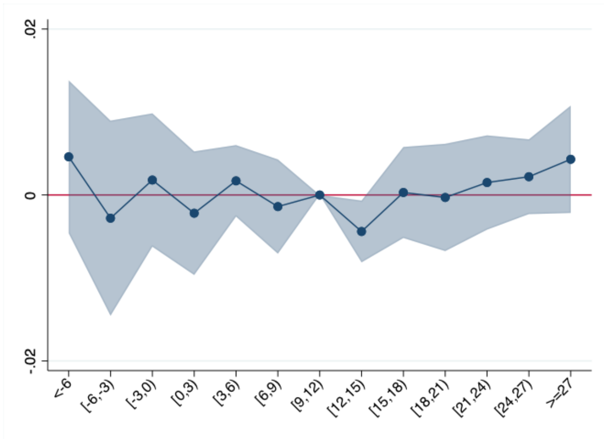
Note: The figure shows the point estimates and the 95% confidence interval of β_b in Equation (1), with the outcome variable being the probability of exit (%). We define exit in year t as a dummy equal to 1 if plant i has positive employment in the LBD in year t but no recorded employment in year $t+1$. The temperature bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Standard errors are clustered at the state level.

Figure XVI: Heterogeneous effects of year-to-year temperature changes on exit

(a) Employment < 20



(b) Employment < 50



Note: The figures report the point estimates and the 95% confidence interval of year-to-year changes in the number of days when the average daily temperature for each zip-code fell within each temperature bin on the x-axis for different subsamples. The outcome variable is the probability of exit (%). Figure (a) only uses the sample with an employment size below 20 for estimation, and Figure (b) only includes plant with below-50 employment. The bin [9°C,12°C) is used as the reference bin. Control variables include the average precipitation, number of hurricanes, and number of tornadoes in the year. Plant, state-year, and industry-year fixed effects are included in all specifications. Standard errors are clustered at the state level.

VII Tables

Table I: Summary Statistics

Variables	N	Mean	Sd
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 difference between the 1980s and the 2010s			
Δ Degree-Days > 18 °C / 100	2800	1.197	1.058
Δ Degree-Days < 18 °C / 100	2800	-2.399	1.536
Δ Log(# Estab.)	2800	-0.0087	0.389
Δ Log(Emp.)	2800	-0.241	0.721
Δ Log(Avg. Size of Estab.)	2800	-0.235	0.61
Δ Fraction of Emp. in Top 5 Largest Estab.	2800	-0.0111	0.112
Δ Log(HHI_Emp.)	2800	-0.0349	0.563
Δ Log(# Estab. of Size < 20)	2800	0.042	0.438
Δ Log(# Estab. of Size ≥ 20)	2800	-0.111	0.589
Δ Log(Emp. in Estab. of Size < 20)	2800	-0.0045	0.495
Δ Log(Emp. in Estab. of Size ≥ 20)	2800	-0.289	0.757
Δ Log(# Estab. of Size < 50)	2500	0.0355	0.394
Δ Log(# Estab. of Size ≥ 50)	2500	-0.198	0.653
Δ Log(Emp. in Estab. of Size < 50)	2500	-0.0072	0.501
Δ Log(Emp. in Estab. of Size ≥ 50)	2500	-0.312	0.752

Table II: Effects of year-to-year temperature changes on energy costs

Dep. Var.	Energy Costs/TVS			
	(1)	(2)	(3)	(4)
T < -6 °C	0.0004	0.0008	0.0014	0.0014
	(0.0007)	(0.0006)	(0.0015)	(0.0015)
-6 °C ≤ T < -3 °C	0.0009	0.0008	0.0001	0.0001
	(0.0009)	(0.0009)	(0.0018)	(0.0018)
-3 °C ≤ T < 0 °C	0.0002	0	-0.0004	-0.0004
	(0.0006)	(0.0006)	(0.0011)	(0.0011)
0 °C ≤ T < 3 °C	0.0008	0.0008	0.0008	0.0008
	(0.0005)	(0.0005)	(0.0009)	(0.0009)
3 °C ≤ T < 6 °C	0.0006	0.0003	0.0003	0.0003
	(0.0006)	(0.0006)	(0.0007)	(0.0007)
6 °C ≤ T < 9 °C	0.0004	0.0003	0.0005	0.0004
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
12 °C ≤ T < 15 °C	0.0008	0.0009**	-0.0001	-0.0001
	(0.0005)	(0.0004)	(0.0007)	(0.0007)
15 °C ≤ T < 18 °C	0.0013***	0.0012**	0.0007	0.0007
	(0.0005)	(0.0004)	(0.0009)	(0.0009)
18 °C ≤ T < 21 °C	0.0015***	0.0014***	0.0017**	0.0016**
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
21 °C ≤ T < 24 °C	0.0017***	0.0015***	0.0021***	0.0021***
	(0.0005)	(0.0005)	(0.0008)	(0.0008)
24 °C ≤ T < 27 °C	0.0013***	0.0013***	0.0026***	0.0026***
	(0.0004)	(0.0004)	(0.0008)	(0.0008)
T ≥ 27 °C	0.0007	0.0008	0.0023*	0.0023*
	(0.0006)	(0.0005)	(0.0013)	(0.0013)
Obs	1922000	1922000	1922000	1922000
R-squared	0.786	0.793	0.795	0.795
Establishment FE	yes	yes	yes	yes
Year FE	yes			
NAICS4-Year FE		yes	yes	yes
State-year FE			yes	yes
Extreme weather controls				yes
Se. cluster level	State	State	State	State
Sample period	1977-2018	1977-2018	1977-2018	1977-2018

Notes: Independent variables are number of days when the temperature fell into the corresponding temperature bin in each county-year. Regressions are estimated using ASM sample weights. The RHS are divided by 100 to make the results more readable. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table III: Effects of year-to-year temperature changes on productivity

Dep. Var.	Log(TFP)				Log(Value-Added/Total Hours Worked)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T < -6 °C	0.0044	-0.0024	0.0356	0.0361	0.0129	0.0068	0.0365	0.0371
	(0.0125)	(0.0107)	(0.0280)	(0.0281)	(0.0189)	(0.0176)	(0.0430)	(0.0430)
-6 °C ≤ T < -3 °C	-0.0248*	-0.0147	0.018	0.018	-0.0299	-0.0237	0.0168	0.0164
	(0.0136)	(0.0136)	(0.0311)	(0.0312)	(0.0202)	(0.0212)	(0.0441)	(0.0441)
-3 °C ≤ T < 0 °C	0.0004	-0.0029	0.0065	0.0068	0.0024	-0.0025	0.0022	0.0025
	(0.0147)	(0.0133)	(0.0214)	(0.0216)	(0.0197)	(0.0192)	(0.0361)	(0.0363)
0 °C ≤ T < 3 °C	0.0044	-0.0033	-0.008	-0.008	0.0057	0.0027	0.0072	0.0071
	(0.0105)	(0.0090)	(0.0146)	(0.0147)	(0.0133)	(0.0128)	(0.0285)	(0.0284)
3 °C ≤ T < 6 °C	0.0019	0.0012	0.0077	0.0076	0.0035	0.0012	0.0183	0.0183
	(0.0117)	(0.0096)	(0.0111)	(0.0111)	(0.0148)	(0.0137)	(0.0235)	(0.0233)
6 °C ≤ T < 9 °C	-0.0062	-0.0107	0.0045	0.0042	-0.0064	-0.0081	0.0089	0.0088
	(0.0103)	(0.0104)	(0.0132)	(0.0133)	(0.0132)	(0.0126)	(0.0138)	(0.0138)
12 °C ≤ T < 15 °C	-0.0061	-0.0073	0.0011	0.0004	0.0023	-0.0007	-0.0021	-0.0031
	(0.0091)	(0.0086)	(0.0094)	(0.0094)	(0.0141)	(0.0129)	(0.0159)	(0.0158)
15 °C ≤ T < 18 °C	0.0056	-0.0012	-0.0292***	-0.0296***	-0.0117	-0.0131	-0.0426**	-0.0430***
	(0.0129)	(0.0109)	(0.0097)	(0.0096)	(0.0122)	(0.0121)	(0.0159)	(0.0158)
18 °C ≤ T < 21 °C	0	0.0004	-0.0343*	-0.0347*	-0.0024	-0.0027	-0.0454	-0.0460*
	(0.0105)	(0.0093)	(0.0188)	(0.0187)	(0.0134)	(0.0122)	(0.0272)	(0.0272)
21 °C ≤ T < 24 °C	-0.0022	-0.0086	-0.0531***	-0.0539***	-0.0275**	-0.0310**	-0.0851***	-0.0861***
	(0.0119)	(0.0097)	(0.0158)	(0.0157)	(0.0126)	(0.0141)	(0.0161)	(0.0161)
24 °C ≤ T < 27 °C	-0.0042	-0.0101	-0.0573***	-0.0583***	-0.0230*	-0.0246*	-0.0689***	-0.0701***
	(0.0103)	(0.0097)	(0.0165)	(0.0164)	(0.0128)	(0.0132)	(0.0141)	(0.0142)
T ≥ 27 °C	0.0106	0.0068	-0.0413**	-0.0419**	-0.0023	-0.0048	-0.0769***	-0.0777***
	(0.0089)	(0.0088)	(0.0203)	(0.0203)	(0.0125)	(0.0121)	(0.0205)	(0.0207)
Obs	1922000	1922000	1922000	1922000	1922000	1922000	1922000	1922000
R-squared	0.771	0.785	0.787	0.787	0.777	0.781	0.782	0.782
Establishment FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes				yes			
NAICS4-Year FE		yes	yes	yes		yes	yes	yes
State-year FE			yes	yes			yes	yes
Extreme Weather controls				yes				yes
Se. cluster level	State	State	State	State	State	State	State	State
Sample period	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018

Notes: Independent variables are number of days when the temperature fell into the corresponding temperature bin in each county-year. Regressions are estimated using ASM sample weights. The RHS are divided by 100 to make the results more readable. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table IV: Effects of year-to-year temperature changes on employment

Dep. Var.	Log(Total Hours Worked)			
	(1)	(2)	(3)	(4)
T < -6 °C	0.0487**	0.0484**	0.0643	0.0637
	(0.0186)	(0.0181)	(0.0704)	(0.0705)
-6 °C ≤ T < -3 °C	0.0321	0.0382	0.0709	0.0706
	(0.0375)	(0.0339)	(0.0660)	(0.0658)
-3 °C ≤ T < 0 °C	0.0497**	0.0447**	0.0756	0.0753
	(0.0216)	(0.0214)	(0.0472)	(0.0472)
0 °C ≤ T < 3 °C	0.0342	0.0303	0.0418	0.0417
	(0.0207)	(0.0199)	(0.0392)	(0.0391)
3 °C ≤ T < 6 °C	0.0025	0.006	0.0066	0.0068
	(0.0163)	(0.0150)	(0.0283)	(0.0283)
6 °C ≤ T < 9 °C	0.004	0.0033	-0.0247**	-0.0243**
	(0.0135)	(0.0119)	(0.0118)	(0.0118)
12 °C ≤ T < 15 °C	-0.0008	-0.0022	0.0057	0.0066
	(0.0232)	(0.0191)	(0.0158)	(0.0158)
15 °C ≤ T < 18 °C	-0.0249	-0.022	-0.0021	-0.0015
	(0.0166)	(0.0148)	(0.0132)	(0.0131)
18 °C ≤ T < 21 °C	-0.0138	-0.0166	0.0107	0.011
	(0.0196)	(0.0162)	(0.0224)	(0.0222)
21 °C ≤ T < 24 °C	-0.0199	-0.019	0.0122	0.0132
	(0.0199)	(0.0186)	(0.0263)	(0.0261)
24 °C ≤ T < 27 °C	-0.0191	-0.0147	0.0008	0.0019
	(0.0136)	(0.0126)	(0.0312)	(0.0309)
T ≥ 27 °C	-0.0092	-0.0124	-0.025	-0.0243
	(0.0241)	(0.0230)	(0.0322)	(0.0322)
Obs	1922000	1922000	1922000	1922000
R-squared	0.923	0.925	0.925	0.925
Establishment FE	yes	yes	yes	yes
Year FE	yes			
NAICS4-Year FE		yes	yes	yes
State-year FE			yes	yes
Extreme Weather controls				yes
Se. cluster level	State	State	State	State
Sample period	1977-2018	1977-2018	1977-2018	1977-2018

Notes: Independent variables are number of days when the temperature fell into the corresponding temperature bin in each county-year. Regressions are estimated using ASM sample weights. The RHS are divided by 100 to make the results more readable. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table V: Effects of year-to-year temperature changes on entry and exit

Dep. Var.	Entry				Exit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T < -6 °C	-0.0031	-0.003	-0.0063	-0.0063	-0.0052	-0.0053	0.0011	0.0011
	(0.0076)	(0.0076)	(0.0044)	(0.0044)	(0.0042)	(0.0043)	(0.0043)	(0.0044)
-6 °C ≤ T < -3 °C	-0.0118	-0.0116	-0.0056	-0.0055	-0.0076	-0.0077	-0.0084	-0.0084
	(0.0094)	(6)	(0.0043)	(0.0043)	(0.0051)	(0.0051)	(0.0073)	(0.0073)
-3 °C ≤ T < 0 °C	-0.0045	-0.0045	-0.005	-0.005	-0.0024	-0.0024	-0.0011	-0.0011
	(0.0061)	(0.0062)	(0.0035)	(0.0035)	(0.0036)	(0.0036)	(0.0037)	(0.0037)
0 °C ≤ T < 3 °C	-0.0026	-0.0025	-0.0048	-0.0048	-0.0064**	-0.0064**	-0.0029	-0.0029
	(0.0055)	(0.0055)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0032)	(0.0032)
3 °C ≤ T < 6 °C	-0.0001	-0.0002	-0.0049*	-0.0049*	-0.0002	-0.0001	0.0017	0.0018
	(0.0052)	(0.0051)	(0.0028)	(0.0028)	(0.0020)	(0.0020)	(0.0022)	(0.0022)
6 °C ≤ T < 9 °C	-0.0005	-0.0006	-0.003	-0.0032	-0.0007	-0.0006	-0.0009	-0.0008
	(0.0028)	(0.0027)	(0.0020)	(0.0020)	(0.0024)	(0.0024)	(0.0029)	(0.0028)
12 °C ≤ T < 15 °C	-0.0028	-0.0028	-0.0042***	-0.0043***	-0.0047	-0.0046	-0.0029	-0.0029
	(0.0020)	(0.0020)	(0.0013)	(0.0013)	(0.0032)	(0.0032)	(0.0019)	(0.0019)
15 °C ≤ T < 18 °C	-0.0059**	-0.0059**	-0.0102***	-0.0102***	-0.0017	-0.0017	0.0015	0.0015
	(0.0024)	(0.0025)	(0.0025)	(0.0025)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
18 °C ≤ T < 21 °C	-0.0085***	-0.0085***	-0.0122***	-0.0123***	-0.0007	-0.0006	0.0005	0.0005
	(0.0026)	(0.0026)	(0.0022)	(0.0022)	(0.0027)	(0.0027)	(0.0032)	(0.0032)
21 °C ≤ T < 24 °C	-0.0068**	-0.0068**	-0.0118***	-0.0119***	0.0005	0.0006	0.0015	0.0015
	(0.0032)	(0.0032)	(0.0029)	(0.0029)	(0.0030)	(0.0030)	(0.0025)	(0.0024)
24 °C ≤ T < 27 °C	-0.0016	-0.0017	-0.0072***	-0.0074***	0.0021	0.0022	0.0029	0.003
	(0.0041)	(0.0041)	(0.0027)	(0.0027)	(0.0042)	(0.0042)	(0.0028)	(0.0028)
T ≥ 27 °C	-0.0035	-0.0035	-0.0083**	-0.0083**	0.0014	0.0015	0.0052	0.0052
	(0.0046)	(0.0046)	(0.0032)	(0.0032)	(0.0053)	(0.0052)	(0.0038)	(0.0039)
Obs	1922000	1922000	1922000	1922000	1922000	1922000	1922000	1922000
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
State-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Extreme weather controls		yes		yes		yes		yes
Se. cluster level	State	State	State	State	State	State	State	State
Sample period	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018	1977-2018

Notes: Dependen variable *Entry* in columns (1)-(4) is an indicator of plant entry at t, where employment of the firm in year t-1 is zero and in year t is above zero. Dependent variable *Exit* in columns (5)-(8) is an indicator of establishment exiting at t, where employment of the firm in year t is above-zero and in year t+1 is zero. Independent variables are number of days when the temperature fell into the corresponding temperature bin in each county-year. The RHS are divided by 100 to make the results more readable. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table VI: Heterogeneous effects of long-run changes in average temperature on number of plants and employment

Panel A: Heterogeneity by establishment size of less or more than 20 workers

Dep. Var.	Δ Log(# Estab. of Size $<$ 20)		Δ Log(# Estab. of Size $\geq$ 20)		Δ Log(Emp. in Estab. of Size $<$ 20)		Δ Log(Emp. in Estab. of Size $\geq$ 20)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Degree-Days $>$ 18 °C / 100	-0.0494**	-0.0399*	-0.0073	0.0005	-0.0668**	-0.0559**	0.0573*	0.0613*
	(0.0209)	(0.0213)	(0.0271)	(0.0257)	(0.0261)	(0.0278)	(0.0316)	(0.0310)
Δ Degree-Days $<$ 18 °C / 100	-0.0253*	-0.0196	0.0041	0.0115	-0.0259*	-0.0215	0.0310*	0.0366**
	(0.0149)	(0.0149)	(0.0133)	(0.0125)	(0.0140)	(0.0143)	(0.0165)	(0.0160)
Obs	2800	2800	2800	2800	2800	2800	2800	2800
R-squared	0.125	0.138	0.179	0.193	0.094	0.101	0.181	0.186
State FE	yes	yes	yes	yes	yes	yes	yes	yes
County controls		yes		yes		yes		yes
Se. cluster level	State	State	State	State	State	State	State	State

Panel B: Heterogeneity by establishment size of less or more than 50 workers

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	-0.0558***	-0.0432**	-0.0051	-0.0015	-0.0556**	-0.0448	0.0436	0.0568*
	(0.0186)	(0.0201)	(0.0294)	(0.0272)	(0.0247)	(0.0276)	(0.0344)	(0.0336)
Δ Degree-Days $<$ 18 °C / 100	-0.0211**	-0.0165	-0.0137	-0.0048	-0.0007	0.0033	0.0123	0.0172
	(0.0102)	(0.0103)	(0.0153)	(0.0137)	(0.0102)	(0.0104)	(0.0194)	(0.0187)
Obs	2500	2500	2500	2500	2500	2500	2500	2500
R-squared	0.155	0.175	0.173	0.191	0.114	0.127	0.182	0.19
State FE	yes	yes	yes	yes	yes	yes	yes	yes
County controls		yes		yes		yes		yes
Se. cluster level	State	State	State	State	State	State	State	State

Notes: Control variables are at the county level, including long-run changes in average precipitation, percentage of population who 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 China shock between 1990 and 2007 in Autor et al. (2013), and changes in occurrences of hurricanes and tornados between the 1980s and the 2010s. Standard errors clustered at state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table VII: Effect of long-run changes in average temperature on total number of plants, employment and average plant size

Dep. Var.	Δ Log(# Estab.)		Δ Log(Emp.)		Δ Log(Avg. Size of Estab.)	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Degree-Days > 18 °C / 100	-0.0406*	-0.0311	0.0336	0.0441	0.0730***	0.0727***
	(0.0213)	(0.0213)	(0.0373)	(0.0354)	(0.0248)	(0.0242)
Δ Degree-Days < 18 °C / 100	-0.0169	-0.0097	0.0189	0.0264	0.0362**	0.0361**
	(0.0139)	(0.0135)	(0.0206)	(0.0197)	(0.0142)	(0.0139)
Obs	2800	2800	2800	2800	2800	2800
R-squared	0.19	0.211	0.192	0.199	0.114	0.116
State FE	yes	yes	yes	yes	yes	yes
County controls		yes		yes		yes
Se. cluster level	State	State	State	State	State	State

Notes: Control variables are at the county level, including long-run changes in average precipitation, percentage of population who 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 China shock between 1990 and 2007 in Autor et al. (2013), and changes in occurrences of hurricanes and tornados between the 1980s and the 2010s. Standard errors clustered at state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table VIII: Effect of long-run changes in average 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	0.0113**	0.0133***	0.0329	0.0483**
	(0.0047)	(0.0038)	(0.0222)	(0.0206)
Δ Degree-Days < 18 °C / 100	0.0068*	0.0048	0.0158	0.0081
	(0.0034)	(0.0029)	(0.0157)	(0.0143)
Obs	2800	2800	2800	2800
R-squared	0.09	0.12	0.073	0.1
State FE	yes	yes	yes	yes
County controls		yes		yes
Se. cluster level	State	State	State	State

Notes: Control variables are at the county level, including long-run changes in average precipitation, percentage of population who 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 China shock between 1990 and 2007 in Autor et al. (2013), and changes in occurrences of hurricanes and tornados between the 1980s and the 2010s. Standard errors clustered at state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

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 the county-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: County initial characteristics

Dep. Var.	log(pc income)	log(pop)	percentage of pop attended college	ΔIPW
	(1)	(2)	(3)	(4)
Δ Degree-days > 18 / 100	-0.0481	0.121	-0.0292**	-0.410
	(0.0302)	(0.200)	(0.0145)	(0.474)
Obs	3,085	3,085	3,085	3,104
R-squared	0.024	0.110	0.025	0.013

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

Dep. Var.	Δ avg. precipitation	Δ flood	Δ drought	Δ heatwave	Δ hurricane	Δ tornado
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Degree-days > 18 / 100	-0.143***	-0.318	1.507	0.369	0.301	-0.0374
	(0.0392)	(0.623)	(1.720)	(0.645)	(0.445)	(0.477)
Observations	3,105	3,105	3,105	3,105	3,105	3,105
R-squared	0.073	0.024	0.066	0.042	0.011	0.018

Notes: Outcome variables in Column (1)-(3) of Panel A are county characteristics observed in 1980 Census. Outcome variable in 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. Outcome variables in 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 report table easier to read. Standard errors are clustered at the state level. Significance level: *** p<0.01, ** p<0.05, * p<0.1.