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A Panel Analysis of the United States

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Abstract[*]

This paper documents that seasonal temperatures have significant and systematic effects on the U.S. economy, both at the aggregate level and across a wide cross-section of economic sectors. This effect is particularly strong for the summer: an increase of 1^{o} F in the average summer temperature is associated with a reduction in the annual growth rate of state-level output of 0:15 to 0:25 percentage points. When these estimates are combined with projected increases in seasonal temperatures it is found that a reduction of U.S. economic growth by up to one third could occur over the next century.

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1 Introduction

We analyze the effect of average seasonal temperatures on the growth rate of U.S. output. We find that seasonal temperatures, particularly summer temperatures, have significant and systematic effects on the U.S. economy, both at the aggregate level and across a wide cross-section of economic sectors. A 1°F increase in the average summer temperature is associated with a reduction in the annual growth rate of state-level output of 0.15 to 0.25 percentage points.

As global average temperatures are predicted to continue rising over this century, many scholars and policymakers have raised warnings of the potential for dramatic damages to the global economy (e.g., Stern (2007), Field et al. (2014)). The economics literature has documented substantial negative effects of global warming on economic growth in developing economies (e.g., Gallup, Sachs and Mellinger (1999), Nordhaus (2006), Burke et al. (2009), Hsiang (2010), Dell, Jones and Olken (2012)). For the U.S., however, it has been challenging to provide systematic evidence that rising temperatures affect the growth rate of economic activities beyond sectors that are naturally exposed to outdoor weather conditions (see Mendelsohn and Neumann (1999), Schlenker and Roberts (2006; 2009), and Burke and Emerick (2015) for an analysis of an agricultural industry). We contribute to this literature by providing comprehensive evidence that rising temperatures do affect U.S. economic activities, at both the aggregate and industry levels.

We overcome existing challenges by exploiting random fluctuations in seasonal temperatures across years and states. Using a panel regression framework with the growth rate of gross state product (henceforth GSP) and average seasonal temperatures of each U.S. state, we find that summer and fall temperatures have opposite effects on economic growth. An increase in the average summer temperature negatively affects the growth rate of GSP, while an increase in the fall temperature positively affects this growth rate, although to a lesser extent. The different signs of the two effects suggest that previous studies' aggregation of temperature data into annual temperature averages (e.g., Dell et al. (2012)) may mask the heterogeneous effects of different seasons.

The summer effect dominates the fall effect in our recent sample (post-1990), leading to a negative net economic effect of rising temperatures. This implies that the U.S. economy is still sensitive to temperature increases, despite the progressive adoption of adaptive technologies such as air conditioning (Barreca et al. (2015)). We also document that the temperature effects are particularly strong in states with relatively higher summer temperatures, most of which are located in the South.

We revisit the conjecture that only a small fraction of the sectors of the economy are sensitive to rising temperatures in developed economies, implying that the aggregate economic impact of warming on the U.S. will be limited (Schelling (1992), Mendelsohn (2010), Nordhaus (2014)). Our results show that rising summer temperatures have a pervasive effect in the entire cross-section of industries, above and beyond the sectors that are traditionally deemed as vulnerable to changing climatic conditions. Specifically, we document that an increase in the average summer temperature negatively affects the growth rate of output of many industries, including food services, insurance carriers, retail, wholesale, and real estate, which in total account for more than a third of national gross domestic product (GDP). These effects are particularly strong for the most recent part of our sample. Only a limited number of sectors, such as utilities (1.8% of national GDP), which includes providers of energy, benefit from an increase in the average summer temperature.

We document that temperature may affect economic activities through its impact on labor productivity. In our empirical analysis, an increase in the average summer temperature decreases the annual growth rate of labor productivity, while an increase in the average fall temperature has the opposite effect. While our finding sheds light on the effects of temperature on labor productivity at the macroeconomic level, it is also consistent with existing studies of this relationship at the microeconomic level. For example, Zivin and Neidell (2014) have found that warmer temperatures reduce labor supply in the U.S., and Cachon, Gallino and Olivares (2012) and Zivin, Hsiang and Neidell (2015) have documented that high temperatures decrease productivity and performance.

Our paper also contributes to the growing debate on the long-term economic consequences of rising global temperatures (e.g., Mendelsohn and Neumann (1999) and Tol (2010)). We combine our estimates of the effects of seasonal temperatures on the growth rate of U.S. output with several projections of the expected U.S. temperature change over the next century. We conduct our analysis under a "business as usual" benchmark, in which there is no additional mitigation and the estimated effects of temperature on economic growth remain unchanged over the long-horizon. We document that the projected increases in summer and fall temperatures could reduce the growth rate of annual nominal GDP by up to 1.5 percentage points, which is more than a third of the historical average nominal growth rate of about 4% per year.

Our analysis highlights the complex ways in which temperatures affect economic activities, and it reveals the need to disaggregate the data into seasons and industries to uncover the full extent of this impact. By providing specific estimates on the effect of temperature on economic activities in the U.S., our empirical analysis informs a growing body of literature focused on general equilibrium models of climate change, including integrated assessment models. These models constitute the basis of many policy recommendations regarding the regulation of greenhouse gas emissions (e.g., Golosov et al. (2014), Acemoglu et al. (2012), Bansal and Ochoa (2011), and Bansal, Ochoa and Kiku (2014)). All of these models critically rely on empirical estimates of the impacts of rising temperatures on aggregate economic activities. In the absence of specific estimates for the U.S., the parameters of these "climate damage functions" are generally calibrated to match cross-country estimates (e.g., Nordhaus and Sztorc (2013)). In this respect, our analysis helps bridge the gap between the theoretical and empirical literatures and will enable researchers to sharpen the policy recommendations based on this class of models, especially for the U.S.

Our paper is related to the analysis of Deryugina and Hsiang (2014), who also exploit within-country variations in the U.S. to find that daily temperatures above certain thresholds reduce county income levels. Our analysis differs from theirs along several dimensions. First, while Deryugina and Hsiang (2014) focus on high-frequency (daily) temperature fluctuations, we focus on a lower frequency (quarterly). This allows us to combine our estimates with existing climatological projections, which are typically only available at lower frequencies. Additionally, we provide a comprehensive industry analysis that documents the widespread and heterogeneous impacts of rising summer temperatures on the cross-section of industries.

In addition, following the extremely cold winters of 2013–2014, the impact of weather-related variables on economic activity has captured the attention of the Federal Reserve Bank (see, for example, Yellen (2014)). Bloesch and Gourio (2015) analyze the impact of temperature and snowfall during the coldest months of the year (November through March) on the growth rate of quarterly economic activities. They find that snowfall has a negative effect on some routinely employed economic indicators such as nonfarm payroll, housing permits, and housing starts. Our analysis is broadly consistent with their results, which suggests that a drop in temperatures in cold weather seems to have a negative impact on economic activities. While they focus on the quarter-to-quarter effect of temperature on economic activity to measure a potential bounce-back effect following adverse winter weather conditions, we assess the cumulative effect on the annual growth rate of output and emphasize the effect of summer temperatures.

The rest of the paper is organized as follows. Section 2 provides a description of the main datasets that we employ in our analysis. Section 3 describes our main results and documents the stability of the estimated effects over time. Section 4 documents several economic mechanisms driving the main results, including the effect of temperature on labor productivity, on the growth rate of output in the cross-section of industries, and in the cross-section of U.S. regions. Section 5 provides evidence that seasonal temperatures affect the growth rate and not just the level of GSP, and it analyzes the long-term consequences of global warming for the aggregate U.S. economy, in addition to providing robustness checks of our main results. Section 6 concludes.

2 Data

This section describes our data sources and the procedures we use to aggregate weather-related data. We refer the reader to the appendix for additional details.

2.1 Weather data

We use daily station-level weather data from the National Oceanic and Atmospheric Administration (NOAA) Northeast Regional Climate Center. This dataset contains daily observations on average temperature, precipitation, and snowfall across U.S. weather stations. Throughout the paper, the unit of temperature is degrees Fahrenheit. The longest common sample across all weather stations starts in 1869 and ends in 2012. In this study, we focus on the 1957–2012 sample, which coincides with the period for which we have data on GSP (see below). For each weather station, we deseasonalize the raw data by regressing daily observations on 12 dummies representing the months of the year and subtract the corresponding estimated monthly component from each observation (see appendix A.2.1 for details on deseasonalization).

We aggregate daily weather observations to quarterly averages by taking the average of the daily observations in each season. Specifically, we define the winter as January through March, the spring as April through June, the summer as July through September, and the fall as October through December. Our definition of seasons coincides with the definition of quarters commonly encountered in the macroeconomics literature, and thus will allow our analysis to contribute to future developments of macroeconomic models that include climate-related variables. We consider alternative definitions of seasons in the robustness checks in section 5.3.

We analyze average seasonal temperatures in order to establish a connection between long-term temperature changes and economic activities. This connection can be more accurately assessed using a lower-frequency temperature measure. To aggregate weather data from the station level to the county and state level, we employ ArcGIS, a geographic information system, to obtain the coordinates for the centroid of each of the 3,144 counties and county equivalents, as well as each weather station. The country, state, and county borders used in ArcGIS are from 2013 topographically integrated geographic encoding and referencing (TIGER) shape files. These shape files, along with the area and population of each county are obtained from the U.S. Census Bureau. We then follow a standard aggregation method (e.g., Deschênes and Greenstone (2012)). For each county we weight the daily temperature, precipitation, and snowfall of each weather station in a 500 km radius of the county's centroid by the inverse of the straight-line distance between the station and the county centroid. In this way, the closest weather stations are assigned a larger weight in determining each county's weather.

Finally, to aggregate to the state level, we weight the weather observations of each county in a state in proportion to either the corresponding county's area or population. Weighting by area assigns larger weights to larger counties, while weighting by population assigns larger weights to more densely populated areas. We use area weights in the main analysis in the text, but our results are very similar across different weighting schemes (see section 5.3). We aggregate state-level weather data to the country level by following the same procedure.

In section 5.3, we document that our results are robust to using non-deseasonalized gridded temperature data. We use the NOAA U.S. Climate Divisions' nClimDiv dataset, which provides absolute monthly temperature averages for each state, derived from area-weighted averages of 5km $\times$ 5km grid-point temperature estimates interpolated from station data.[1]

2.2 State-level economic data

We use data on nominal GSP between 1957 and 2012 for all 50 states and the District of Columbia. GSP is defined as the value added in production by the labor and capital of all industries located in that state. Data for 1957–1962 come from the U.S. Census Bureau Bicentennial Edition, and data for the 1963–2012 sample come from the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). The data frequency is annual. From the BEA, we also collected data for national GDP, nominal GSP per capita, real GSP, and industry output data for the 1963–2011 sample. Industry data for 1963–1997 are categorized using the Standard Industrial Classification (SIC) codes, while data for 1997–2011 follow the North American Industry Classification System (NAICS). Finally, annual employment data at the state level (measured in thousands of employees) are collected from the Bureau of Labor and Statistics for the sample 1990–2012.

3 Main results

In this section we report our main empirical results. First, as a benchmark, we show that the relationship between temperatures and growth is not statistically significant in time-series regressions at the whole-country level, consistent with findings in the exist-

[1] See `ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-inv-readme.txt` for more details.

Table 1: Main Results
Effects of annual and seasonal temperatures on GSP growth

	Whole Year	**Winter**	**Spring**	**Summer**	**Fall**
Time Series	−0.396	−0.071	−0.027	−0.414	0.042
	(0.382)	(0.179)	(0.334)	(0.385)	(0.287)
Panel Analysis	0.006	0.001	0.003	−0.154	0.102
	(0.111)	(0.049)	(0.065)	(0.072)**	(0.055)*
	(0.069)	(0.025)	(0.032)	(0.047)***	(0.040)**

Notes: The first column reports the estimated coefficients on average annual temperature from a regression of the economic growth rate on its lag and the average annual temperature (regressions (1) and (3)). The four columns on the right report the estimated coefficients for each of the four seasonal temperature averages (regressions (2) and (4)). The top panel ("Time Series") reports the estimated coefficients using GDP and weather data aggregated to the national level (regressions (1) and (2)). The bottom panel ("Panel Analysis") reports estimated coefficients using state-level GSP and weather data (regressions (3) and (4)). In the panel regressions, all 50 states and the District of Columbia are included and each state is weighted by the proportion, averaged over the whole sample, of its GSP relative to the national GDP. All specifications include the lagged dependent variable, and the panel specifications include state and year fixed effects. Temperatures are in degrees Fahrenheit. The sample is 1957–2012. Standard errors are in parentheses. In the bottom panel, the first standard error beneath each estimated parameter is clustered by year, while the second is clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

ing literature. Then, we improve the analysis by using panel regressions with weather and economic data from all 50 states plus the District of Columbia (henceforth "the cross-section of states"). Our main findings are as follows: (1) an increase in the average summer temperature negatively affects the growth rate of GSP, and (2) an increase in the average fall temperature positively affects growth, although to a lesser extent. Both effects are statistically and economically significant. In section 5.3, we perform a comprehensive set of robustness checks and show that the summer effect is generally very robust, while the fall effect is less so.

3.1 Benchmark: Time-series regressions with country-level data

We consider two time-series regressions. The first is a regression of the aggregate growth rate of national GDP on the average annual temperature:

$$\Delta y_t = \beta T_t + \rho \Delta y_{t-1} + \varepsilon_t, \tag{1}$$

where Δy_t denotes the growth rate of national GDP between years $t-1$ and t; T_t denotes the annual average temperature in year t in degrees Fahreneit; and the lagged growth rate Δy_{t-1} controls for autocorrelation.

The second is a regression of the growth rate of aggregate GDP on the average temperatures of the four seasons:

$$\Delta y_t = \sum_{s \in \mathcal{S}} \beta_s T_{s,t} + \rho \Delta y_{t-1} + \varepsilon_t, \tag{2}$$

where $T_{s,t}$ denotes the average temperature in season $s \in \mathcal{S} = \{winter, spring, summer, fall\}$ in year t.

The first row of table 1 reports the results of these regressions. The column "Whole Year" reports the estimate for the coefficient β in equation (1). The remaining columns report the estimations for coefficients β_s in equation (2). As the table shows, none of the estimated coefficients are statistically significant. These results confirm the difficulty of identifying the effect of temperature on economic growth in the U.S. documented in the extant literature.

3.2 Panel regressions with state-level data

We explore the impact of temperature on the growth rates of GSP in the cross-section of states using two panel specifications that mirror our time-series analysis. The first is a regression of the growth rate of GSP on the state-level annual average temperature:

$$\Delta y_{i,t} = \beta T_{i,t} + \rho \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{3}$$

where $\Delta y_{i,t}$ and $T_{i,t}$ denote GSP growth and the annual average temperature in state i in year t, respectively, while α_i and α_t denote state and year fixed effects. We again include the lagged GSP growth rate as a control to capture the degree of autocorrelation of the dependent variable.

In the second specification, which is the main specification of the paper, we disaggregate the annual average temperature into four average seasonal temperatures:

$$\Delta y_{i,t} = \sum_{s \in \mathcal{S}} \beta_s T_{i,s,t} + \rho \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{4}$$

where the variables are defined as above and $T_{i,s,t}$ denotes the temperature in degrees Fahrenheit in state i, year t, and season s.

Since some states have larger GSPs and thus contribute more to national GDP than others, in both panel specifications we weight each state by the proportion of its GSP relative to the entire country's GDP over the whole sample (see appendix A.2.2 for details). In section 5.3 we conduct robustness checks with alternative weighting schemes.

We report the results of these panel regressions in table 1. The column "Whole Year" refers to the specification in equation (3). We report the estimated coefficient for β and standard errors, clustered first by years and then by state. The results indicate that the effect of average temperature at the annual level is again not statistically significant, confirming the findings in the time-series specifications.

However, when we break down annual temperatures into the four seasonal temperatures, the results change substantially. The rightmost four columns of table 1 report the estimates for the β_ss seasonal coefficients with associated standard errors, clustered by year and by state. The table shows the relationship between average summer and fall temperatures and economic growth rates. These effects are both statistically and economically significant: a 1^{o}F increase in the average summer temperature is associated with a reduction in the annual GSP growth rate by 0.154 percentage points, while a 1^{o}F increase in the average fall temperature is associated with an increase in the annual GSP growth rate by 0.102 percentage points.

The opposite direction of the impact of summer and fall temperatures on GSP growth rates may partially explain the difficulty of obtaining statistically significant estimates using annual temperatures. Even though the magnitudes of the summer and fall effects are comparable, we document through robustness checks (section 5.3) and the exercise below that the summer effect is much more robust than the fall effect.

3.3 Stability of the effects through time

We explore how the estimated coefficients in panel regression (4) evolve through time. This exploration is relevant because it could be the case that the negative economic effects of summer temperatures are diminished in the more recent part of the sample due to adaptation (for example, due to widespread adoption of air conditioning technologies as documented by Barreca et al. (2015)).

We re-run the regression specified in equation (4) but delay the beginning of the sample by one year at a time. We repeat this exercise until the sample starts in 1990; past this year, the sample size becomes very small, thus compromising the statistical significance of our estimation. The results, reported in figure 1 show that the summer coefficient remains negative and statistically significant at the 10% level as the sample shrinks; the point-estimate for the summer effect is -0.154 in the full sample and -0.254 in the post-1990 sample. However, the fall coefficient is no longer statistically significant in the post-1990 sample; the point-estimate for the fall effect is 0.102 in the full sample

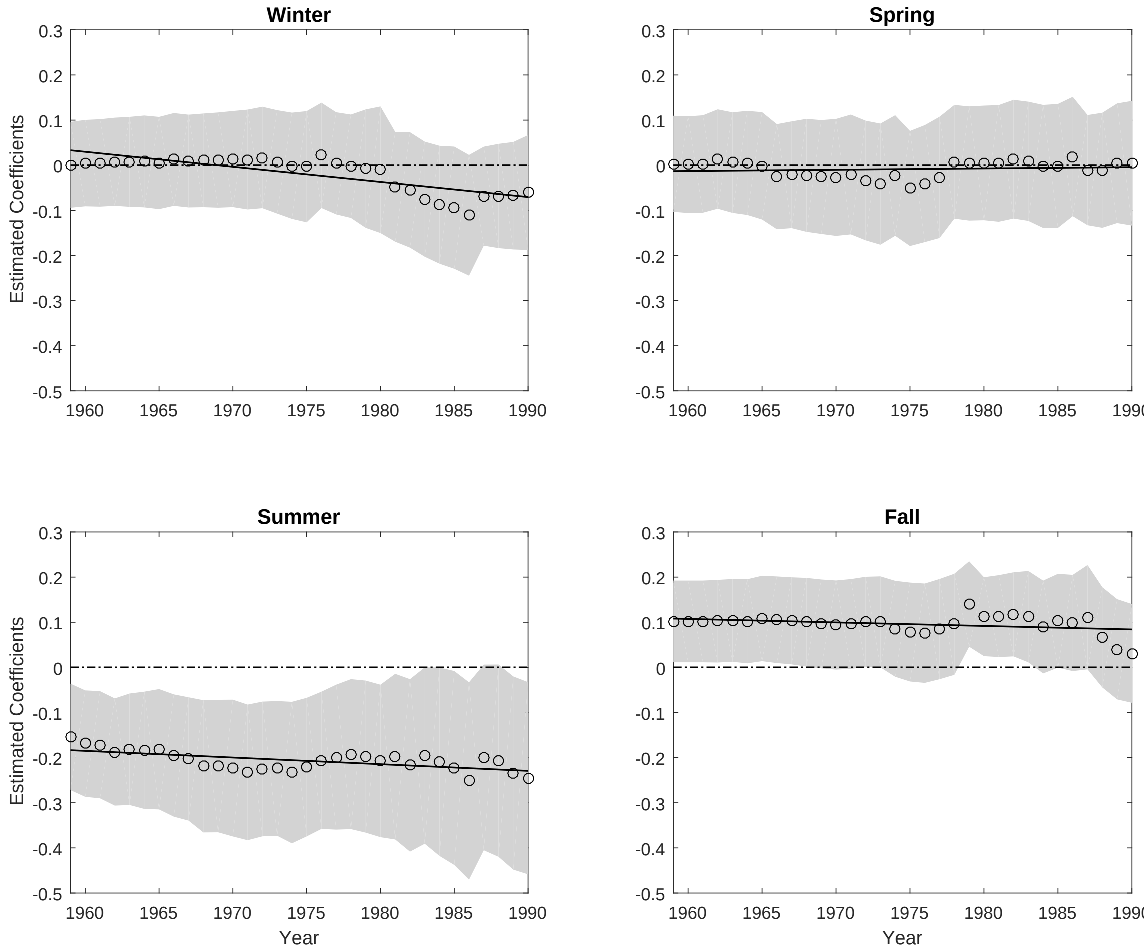

Figure 1: Stability across time of the effect of average seasonal temperatures on GSP growth. Each panel reports the estimated coefficients of average temperature for the corresponding season. Dots correspond to the coefficients estimated over the sample starting with the year reported on the horizontal axis and ending in 2012. The panel regressions are for the entire cross-section of the U.S. Each state is weighted by its relative GSP. Regressions include state and year fixed effects. The grey areas represent 90% confidence intervals. Standard errors are clustered at the year level. The solid lines are linear fits of the dots in each panel.

and 0.031 (and indistinguishable from zero) in the post-1990 sample. This finding is consistent with the results of our robustness checks (section 5.3): the summer effect is very robust, but the fall effect is not.

4 Economic mechanisms

In this section, we explore potential mechanisms through which temperatures affect the growth rate of GSP. First, we show that summer and fall temperatures affect the growth of labor productivity. Second, we disaggregate GSP into industry groups and show that, in the post-1997 sample, an increase in the average summer temperature negatively affects output growth in various industry groups (including food services and drinking places; insurance; wholesale; retail; and agriculture, forestry, and fishing) and positively affects growth in the utilities and mining sectors. Third, we show that the effect of temperature on GSP is particularly strong in Southern states.

4.1 Effect on labor productivity

We study the possibility that temperature affects economic growth through labor productivity. Following Bernard and Jones (1996), we define labor productivity for each state as the ratio between total private industry output and employment. The decision to restrict our focus to private industries is dictated by the fact that the Bureau of Labor Statistics reports data on state-level employment only for private industries. We verify in our robustness checks (see section 5.3) that the main results reported in table 1 are still valid for this specific subset of industries. Similarly, our choice to analyze labor productivity as opposed to total factor productivity is based on data availability.[2]

In the top panel of table 2 we report the results of our analysis of the growth rate of annual labor productivity. Specifically, we estimate the coefficients of the following specification:

$$\Delta a_{i,t} = \sum_{s \in \mathcal{S}} \beta_s T_{i,s,t} + \rho \Delta a_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{5}$$

[2]Garofalo and Yamarik (2002) built a dataset for state-level real capital stock. However, the sample over which real GSP and real capital stock are deflated using the same method is limited, thus impairing the construction of a panel of total factor productivity series.

where $\Delta a_{i,t}$ denotes the growth rate of productivity in state i at year t, and all other variables are defined as in the previous sections. Specification (5) corresponds to our baseline specification in (4) but replaces the growth rate of GSP with the growth rate of productivity. The last two columns of table 2 document that summer and fall temperatures again have significant effects on the growth rate of labor productivity. These results confirm our findings in table 1 and also provide a possible pathway through which seasonal temperatures may affect economic growth. Specifically, an increase in the average summer temperature negatively affects productivity growth, which in turn results in a reduction in output. A drop in the average fall temperature seems to be detrimental for productivity, thus resulting in a lower growth rate of GSP.

The bottom panel of table 2 reports the results of our analysis of the growth rate of employment for private industries. The estimates in this panel correspond to the specification in equation (4), except that the dependent variable is the growth rate of employment rather than the growth rate of GSP. The results indicate that the association between average summer and fall temperatures and the growth rate of employment is not statistically significant. Taken together, the results in the top and bottom panels of table 2 suggest that a main mechanism through which summer and fall temperatures affect GSP growth is productivity growth, rather than employment growth.

Our results are in line with other findings in the literature. For example, Cachon et al. (2012) document that heat and snow significantly affect output and productivity in automobile plants. The occurrence of six or more days with temperatures above 90 degrees Farenheit reduces the weekly production of U.S. automobile manufacturing plants by an average of 8 percent. Given that automobile manufacturing largely takes place indoors, the authors argue that this finding suggests there are limitations of air conditioning; it is possible that there are important areas in the production process, such as loading and unloading areas, that are difficult to cool or warm. Bloesch and Gourio (2015) also document that cold weather negatively affects production in various industries. We will

Table 2: Effects of temperatures on productivity growth and employment growth

	Winter	Spring	Summer	Fall
Productivity	−0.033	−0.020	−0.152	0.132
	(0.067)	(0.065)	(0.087)*	(0.048)***
	(0.042)	(0.031)	(0.050)***	(0.054)**
Employment	0.013	−0.086	0.008	−0.021
	(0.032)	(0.051)*	(0.059)	(0.042)
	(0.015)	(0.051)*	(0.037)	(0.019)

Notes: This table reports results for panel regressions of state productivity growth rate on temperatures, using the entire cross-section of 50 states and the District of Columbia. Productivity is defined as output over employment in the private sector. All specifications include the lagged dependent variable, state and year fixed effects. States are weighted in the panel regression by the proportion, averaged over the whole sample, of their GSP relative to that of the whole country. The columns refer to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as Jan.–Mar., spring as Apr.–Jun., summer as Jul.–Sep., fall as Oct.–Dec. Temperatures are in degrees Fahrenheit. The sample is 1990–2011. Two standard errors, the first clustered by year and the second clustered by state, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

return to this discussion in the industry analysis below.

Several other studies also document effects of temperature on productivity and performance. In a survey of workplace and laboratory studies with objective measures of performance, Seppänen et al. (2006) document that performance at office tasks decreases at high temperatures. Similarly, Adhvaryu et al. (2014) find that productivity in garment factories in Bangalore, India, decreases at high temperatures. Using repeated cognitive assessments from the National Survey of Youth, Zivin et al. (2015) study the effect of short-run weather shocks on cognitive performance and find that an increase in outdoor temperature decreases math performance.

4.2 Industry analysis

We further explore the composition of the effects documented in the panel regression in table 1 by breaking down the total GSP of each state into 12 large industry groups. These groups are listed in descending order of national GDP share in the first column of table 3 (for a detailed list of industries in each group, see appendix table A2). The last column of table 3 provides the post-1997 average share of national GDP for each group. These groups are nonoverlapping and together account for 100% of gross product.

One caveat of this exercise is a data limitation due to the change in the classification of industries, from the Standard Industrial Classification system (SIC) to the North American Industry Classification System (NAICS), that took place in 1997. In several instances this substantially affects the composition of specific industries (see the breakdowns of the "Services" and "Communication/Information" categories in appendix table A2). In order to prevent our results from picking up effects that may be due to these changes, we report the results of our analysis over two separate subsamples (pre- and post-1997). This split significantly reduces the sample size and, hence, the power of our statistical analysis. For this reason, we estimate only the effect of summer temperature—the season whose effects on economic growth is strongest in our analysis. Specifically, for each group of industries j, we estimate the following equation:

$$\Delta y_{i,t}^{j} = \beta_{summer}^{j} T_{i,summer,t} + \rho \Delta y_{i,t-1}^{j} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{6}$$

where $\Delta y_{i,t}^{j}$ denotes the output growth of industry group j in state i at year t.

Our results for the estimate of β_{summer}^{j} for each industry group are reported in table 3. The columns labeled "Pre-1997" and "Post-1997" correspond to the estimates for the 1963-1997 and 1997-2011 samples, respectively. As before, for each coefficient estimate, we report two standard errors, the first clustered by year and the second clustered by state.

Several important findings emerge from table 3. First, an increase in the average summer temperature has a substantial negative effect on agriculture, forestry, and fishing (see the last row of table 3). While the effect on this sector is intuitive and well studied in the literature, we note that this sector only accounts for about 1% of national GDP (see, inter alia, Mendelsohn and Neumann (1999), Schlenker and Roberts (2006; 2009), and Burke and Emerick (2015)).

Second, an increase in the average summer temperature also negatively affects the retail and wholesale sectors, which account for 6.6% and 5.9% of national GDP, respectively. There are several possible explanations for these effects. On the one hand, from a psychological perspective, high temperatures may negatively affect customers' perception of wait time (Baker and Cameron (1996)) and social interactions with strangers (Griffit and Veitch (1971)). Thus, from a household production perspective (Ghez and Becker (1975)), high temperatures may adversely impact what Starr-McCluer (2000) calls "households' shopping productivity," inducing them to spend less time shopping and therefore reducing retailers' revenues. On the other hand, high summer temperatures may negatively affect the productivity of workers in what Cachon et al. (2012) call interface areas, such as loading and unloading areas, which are difficult to cool with air conditioning. This mechanism may also explain why the construction sector, which accounts for 4.4% of national GDP, appears to be negatively affected by an increase in the average summer temperature.

The two largest sectors of the U.S. economy are Services and Finance, insurance, and real estate, accounting together for almost a half of national GDP. These sectors are both negatively affected by an increase in the average summer temperature in the post-1997 sample (see table 3). Table 4 explores this post-1997 negative relationship in greater detail, by further decomposing the two sectors into an exhaustive list of subcomponents.

An increase in summer temperature negatively affects Food services and drinking places, which account for about 2% of national GDP (table 4). This could be a reflection of the negative impact of high temperatures on agricultural output. As the supply of agriculture-related products declines, prices increase, and if the establishments operating in the food services sector cannot immediately adjust their prices, they will experience a decline in their profitability and may decrease production.[3]

Furthermore, an increase in summer temperatures has a substantial and negative effect on the insurance sector, which accounts for about 2.6% of national GDP. One potential explanation is that health insurance companies may have to make more payouts due to the increased number of heat-induced hospitalizations. Two recent studies conducted for the state of Washington have documented that hot, humid days increase the risk of hospitalization and death (Isaksen et al. (2015a; 2015b)). Choudhary and Vaidyanathan (2014) provide evidence that increases in summer temperatures are associated with an increase in heat stress illness (HSI) hospitalizations.[4] Focusing on community hospitals, Merrill et al. (2008) report that the hospitalization costs from exposure to heat are in the order of $40 million per year, billed roughly equally to government payers (Medicare and Medicaid) and private insurance companies.

The real estate sector, which accounts for about 11.4% of national GDP, seems to be negatively affected by an increase in the average summer temperature. The real estate market is characterized by a "search-and-match" mechanism, a large part of which takes place outdoors, and many prospective home-buyers search for houses in the summer (Ngai and Tenreyro (2014)). Higher summer temperatures may negatively affect prospective home-buyers' productivity in searching, thus impacting the overall sales volume of this market.

Not all industry groups are negatively affected by an increase in summer temperatures. The utilities and mining sectors, accounting for about 1.8% and 1.4% of national GDP, respectively, appear to benefit from an increase in the average summer temperature (see table 3). This could be due to the higher consumption of energy during warmer summers, which translates into larger revenues for these industries.

[3]A psychological mechanism similar to the one mentioned above for the retail sector could also lead to a decline in the demand for food services and drinking place in hot summer temperatures.

[4]Additionally, Chan et al. (2013) have shown that during the hot season in Hong Kong, hospital admissions increased by 4.5% for every increase of 1 degree Celsius above the seasonal average temperature.

Table 3: Industry group analysis

	Pre-1997	Post-1997	Avg. GDP share (post-97, %)
Services†	0.020	−0.206	25.7
	(0.070)	(0.075)***	
	(0.050)	(0.076)***	
Finance, insurance, real estate	−0.209	−0.437	20.5
	(0.241)	(0.384)	
	(0.228)	(0.158)***	
Manufacturing	−0.058	0.067	12.9
	(0.215)	(0.623)	
	(0.102)	(0.420)	
Government	−0.068	−0.051	12.2
	(0.071)	(0.165)	
	(0.063)	(0.086)	
Retail	−0.052	−0.241	6.6
	(0.073)	(0.189)	
	(0.060)	(0.083)***	
Wholesale	−0.158	−0.284	5.9
	(0.104)	(0.171)*	
	(0.062)**	(0.163)*	
Communication/Information†	−0.235	−0.294	4.5
	(0.088)***	(0.732)	
	(0.092)**	(0.405)	
Construction	−0.224	−0.379	4.4
	(0.236)	(0.446)	
	(0.199)	(0.194)*	
Transportation	0.150	0.189	3.0
	(0.125)	(0.221)	
	(0.196)	(0.138)	
Utilities	0.338	0.621	1.8
	(0.248)	(0.377)*	
	(0.202)*	(0.230)***	
Mining	−0.153	0.954	1.4
	(0.539)	(1.524)	
	(0.572)	(0.300)***	
Agriculture, forestry, fishing	−2.489	−2.203	1.1
	(0.995)**	(0.969)**	
	(0.443)***	(0.502)***	

Notes: This table reports results for panel regressions of industry output growth, using the entire cross-section of 50 states and the District of Columbia. All specifications include the lagged dependent variable, and state and year fixed effects; the independent variable is the average summer temperature. In each industry regression, states are weighted in the panel regression by the proportion, averaged over the whole sample, of their industry output relative to that of the whole country. The first column uses the 1963–1997 sample; the second column uses the 1997–2011 sample. The last column reports the share of national GDP that each industry accounts for, averaged over the 1997–2011 sample. Two standard errors, the top clustered by year and the bottom clustered by state, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Industries are classified according to the Bureau of Economic Analysis. †: There are substantial differences between the pre- and post-1997 classifications of these industries; see appendix table A2.

Table 4: Industry group analysis: Services and Finance, insurance, real estate

	Post-1997	Ave GDP share
Services		
Professional and business services	−0.219	11.6
	(0.127)*	
	(0.098)**	
Educational services, health care, social assistance	−0.005	7.7
	(0.047)	
	(0.065)	
Other services, except government	−0.253	2.6
	(0.136)*	
	(0.103)**	
Food services and drinking places	−0.387	2.0
	(0.155)**	
	(0.148)***	
Arts, entertainment, and recreation	0.417	1.0
	(0.274)	
	(0.203)**	
Accommodation	0.025	0.9
	(0.270)	
	(0.359)	
Finance, insurance, real estate		
Real estate	−0.435	11.4
	(0.400)	
	(0.125)***	
Federal Reserve banks, credit intermediation, and related services	−0.254	3.6
	(0.463)	
	(0.354)	
Insurance, carriers and related activities	−1.299	2.6
	(0.631)**	
	(0.548)**	
Securities, commodity contracts, and investments	−0.287	1.3
	(0.531)	
	(0.337)	
Rental and leasing services, lessors of intangible assets	−0.030	1.3
	(0.244)	
	(0.290)	
Funds, trusts, and other financial vehicles	1.027	0.2
	(1.142)	
	(1.068)	

Notes: This table reports results for panel regressions of industry output growth, using the entire cross-section of 50 states and the District of Columbia. Industries are classified according to the Bureau of Economic Analysis (see appendix table A2). All specifications include the lagged dependent variable, and state and year fixed effects; the independent variable is the average summer temperature. In each industry regression, states are weighted in the panel regression by the proportion, averaged over the whole sample, of their industry output relative to the whole country's. The sample is 1997–2011. The last column reports the share of national GDP that each industry accounts for. Two standard errors, the first clustered by year and the second clustered by state, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Overall, our results suggest that the effects of summer temperatures on aggregate economic activity are not due to the isolated impact of rising temperatures on just a few sectors of the economy. Rather, higher temperatures systematically affect a large cross-section of industries, which in total account for more than a third of national GDP.

4.3 Regional analysis

To determine whether certain broad geographic areas are primarily responsible for the effects of seasonal temperatures on GSP, we divide the U.S. into four regions: North, South, Midwest, and West. These regions are identified according to the classification of the U.S. Census Bureau (see appendix A.4 for the list of states in each region). We then estimate the effects of seasonal temperatures for each region using a panel regression of the growth rate of state-level GSP on temperatures.

The results of this regional analysis (reported in table 5) document that the effects of summer and fall temperatures are statistically and economically significant in the South. The estimated coefficients for the South are substantially larger than their country-level counterparts identified in table 1. This indicates that the growth rates of GSP in Southern states are particularly sensitive to summer and fall temperatures, while other regions do not appear to be systematically affected.

We argue that the significance of the estimated coefficients for the South region can be attributed to the relatively higher average temperatures that characterize the states in this area. To provide evidence in support of this claim, we sort states in descending order, according to their average summer temperature. As expected, the states in the South region occupy the highest positions (see appendix table A3). We then estimate the regression coefficients of equation (4) for the ten states with the highest summer temperatures, and successively re-estimate these coefficients, each time adding the next temperature-sorted state. The results of this exercise are reported in figure 2.

Table 5: Effects of seasonal temperatures on GSP growth in different regions

	Winter	Spring	Summer	Fall
North	0.329	0.065	0.240	−0.255
	(0.173)*	(0.296)	(0.257)	(0.233)
	(0.238)	(0.176)	(0.232)	(0.184)
South	−0.087	0.152	−0.326	0.571
	(0.167)	(0.159)	(0.163)**	(0.194)***
	(0.077)	(0.087)*	(0.085)***	(0.063)***
Midwest	0.010	−0.158	0.043	−0.116
	(0.089)	(0.144)	(0.162)	(0.128)
	(0.055)	(0.104)	(0.076)	(0.068)*
West	−0.000	−0.155	0.028	−0.006
	(0.096)	(0.143)	(0.154)	(0.167)
	(0.061)	(0.078)**	(0.145)	(0.162)

Notes: This table reports results for panel regressions of state GSP growth rate on temperatures, using the cross-section of U.S. states in each region. Regions are classified according to the Census Bureau. All specifications include the lagged dependent variable, and state and year fixed effects. States are weighted in the panel regression by the proportion, averaged over the whole sample, of their GSP relative to the region's GDP. The columns refer to the analysis conducted by regressing jointly on the four seasonal averages. Winter is defined as Jan.–Mar., spring as Apr.–Jun., summer is Jul.–Sep., fall is Oct.–Dec. Temperatures are in degrees Fahrenheit. The sample is 1957–2012. Two standard errors, the first clustered by year and the second clustered by state, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

The bottom left panel of figure 2 documents that the estimated summer coefficient for the ten warmest states is about three times as large as their whole-country counterpart. The absolute value of the summer coefficient declines sharply past the first 15 states, thus highlighting a nonlinearity in the impact of rising temperatures for this season. Furthermore, a comparison of the bottom two panels of figure 2 reveals that the dramatic rise of the impact coefficient for the warmest states is precisely identified for the average summer temperature, whereas the coefficient of the average fall temperature is characterized by a higher degree of uncertainty. Winter and spring temperatures do not seem to play a major role in this part of our analysis.

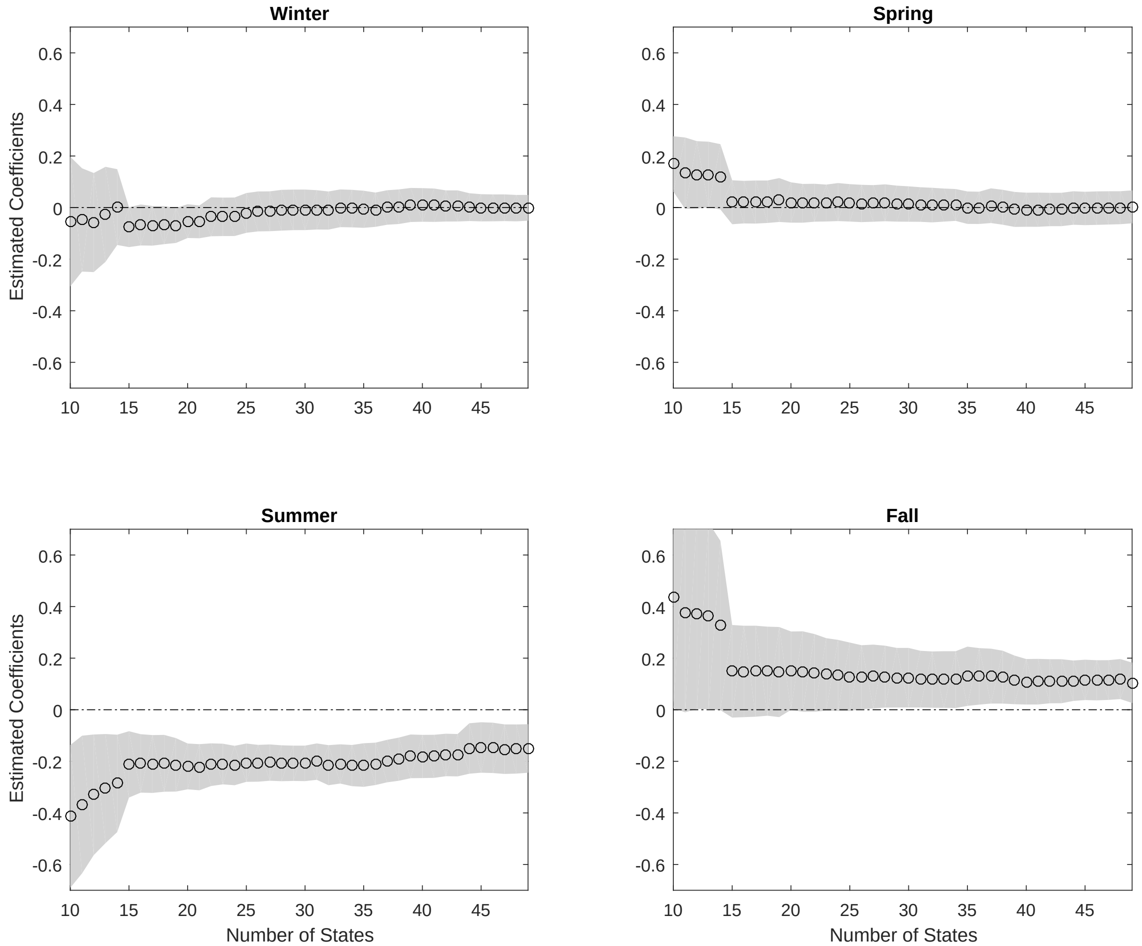

Figure 2: Effects of seasonal temperatures in temperature-sorted states. Each panel reports the estimated coefficients of the average temperature for the corresponding season. Dots corresponds to the coefficients estimated for the number of states reported in the horizontal axis. The grey areas represent 95% confidence intervals. States are sorted in descending order according to their average summer temperature. Each state is weighted by its relative GSP in the panel regressions. State and year fixed effects are included. Standard errors are clustered at the year level.

5 Additional results

In this section we conduct a series of additional exercises to confirm and extend the analysis above. In section 5.1 we document that the temperature effects that we identified are on the growth rate rather than on the level of output. This evidence motivates the exercise in section 5.2, in which we combine the estimated impact coefficients from section 3 with various projections of temperature changes over the next 100 years to provide an assessment of the long-term impact of rising temperature on U.S. economic growth. In section 5.3 we conclude our investigation by showing that our main finding on the effect of summer temperatures is robust to alternative specifications.

5.1 Growth vs. level effects

In this section we test whether the response of GSP to temperature is an effect on the level of output or on its growth rate. It is important to distinguish between these two hypotheses, because the effects on the growth rate compound over time and thus are more quantitatively important than effects on the level of output (Pindyck (2011; 2013), Dell et al. (2012)).

To illustrate the quantitative significance of growth effects compared to level effects, and to set the stage for our empirical methodology, consider the following simple example. Assume that the aggregate output of a certain state follows the process:

$$y_t = \alpha + y_{t-1} + \beta T_t + \beta_{lag} T_{t-1} + \varepsilon_t, \tag{7}$$

where β and β_{lag} denote the impacts of current and lagged average temperatures T (of, for instance, the current and last summer) on output growth. For simplicity, we assume that $\varepsilon_t = 0$, $\forall t$. Consider a shock in year $t = 1$ that permanently increases the average temperature T by one degree Fahrenheit, from $T_0 = 0$ to $T_t = 1, \forall t \geq 1$ (illustrated in the left panel of figure 3). This temperature path is motivated by climatologists' predictions that temperatures will rise permanently by the middle and end of this century (see section 5.2 for details). Along this hypothetical temperature path, the level and the growth rate of output would be

$$
\begin{aligned}
y_t &= (y_0 + \beta) + (t-1)\left[\alpha + (\beta + \beta_{lag})\right], \text{ and} && (8)\\
\Delta y_1 &= \alpha + \beta, \qquad \text{and} \qquad \Delta y_t = \alpha + (\beta + \beta_{lag}), \quad \forall t \geq 2, && (9)
\end{aligned}
$$

respectively. We consider three cases. If $\beta = \beta_{lag} = 0$, then temperatures have no economic effects. We refer to this situation as the No Effect case. If $\beta + \beta_{lag} = 0$, then an increase in temperature has a permanent impact on the level of output (see equation (8)), but it only affects the growth rate of output for one period (see equation (9)). We refer to this situation as the Level Effect case. If $\beta + \beta_{lag} \neq 0$, temperature permanently affects both the level and the growth rate of output. We refer to this situation as the Growth Effect case.

We illustrate these three scenarios in the right panel of figure 3. Over the span of 50 years, if temperatures permanently affect the growth rate of output (the Growth Effect case), then the level of output would be substantially lower than what it would be in the No Effect case (dashed-dot vs. dashed line). This is in sharp contrast to the case in which temperature has a permanent effect only on the level of output (the Level Effect case). In this scenario, after 50 years output is only marginally lower compared to the baseline case (solid vs. dashed line).

We follow the logic of this example to test whether average seasonal temperatures affect the growth rate of GSP in the data. Specifically, we estimate the following equation:

$$
\Delta y_{i,t} = \sum_{s \in \mathcal{S}} \beta_s T_{i,s,t} + \underbrace{\sum_{s \in \mathcal{S}} \beta_{lag,s} T_{i,s,t-1}}_{\text{lagged terms}} + \rho \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{10}
$$

Then we test whether we can reject the null hypothesis that the sum of the contemporaneous and lagged coefficients for each season is equal to zero, that is, $H_0 : \beta_s + \beta_{lag,s} = 0$,

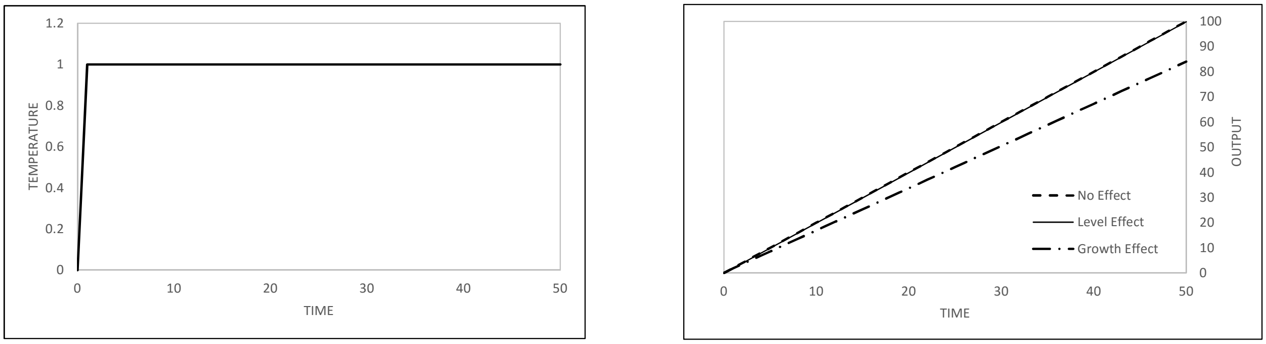

Figure 3: Growth vs. level effect. The left panel depicts a permanent increase of 1 degree Fahrenheit in the level of temperature that takes place at year 1. The right panel shows the levels of output associated with the temperature path reported in the left panel. The three lines are constructed according to equation (7), by setting $\beta = \beta_{lag} = 0$ (dashed line), $\beta = -\beta_{lag} = -0.170$ (solid line), and $\beta = -0.170$, $\beta_{lag} = -0.153$ (dash-dot line). In all three cases $\mu = 2$ and $\varepsilon_t = 0$, $\forall t$.

for each season s.[5]

Our results, reported in table 6, indicate that lagged temperatures are generally statistically significant, with the exception of the winter season. The signs of the effects for summer and fall do not change when considering the lagged temperatures. Most importantly, we can strongly reject the null hypothesis that the sums of the contemporaneous and lagged temperature coefficients are equal to zero ($\beta_s + \beta_{lag,s} = 0$) for summer and fall. This evidence supports the hypothesis that increases in summer and fall temperatures have lasting effects on output growth.

5.2 Combining our results with climate projections

In this section we provide a quantification of the magnitudes of the effects of summer and fall temperatures estimated in panel regression (4) over a longer horizon. This exercise needs to be interpreted with caution, since it assumes that the impact coefficients

[5]Note that by setting $\beta_s \equiv \beta/4$, $\beta_{lag,s} \equiv \beta_{lag}/4$, for each season s, we obtain the specification for average annual temperature in (3) augmented with lagged temperature. We omit this case from our investigation, since we did not find any statistically significant effect associated with annual temperatures in table 1.

Table 6: Growth vs. level effects

	Winter	Spring	Summer	Fall
Contemporaneous temp.	−0.008	−0.012	−0.170	0.109
	(0.051)	(0.059)	(0.076)**	(0.050)**
	(0.029)	(0.032)	(0.045)***	(0.038)***
One-year lagged temp.	0.004	0.121	−0.153	0.066
	(0.053)	(0.063)*	(0.079)*	(0.060)
	(0.023)	(0.039)***	(0.053)***	(0.029)**
Sum of coefficients	−0.040	0.109	−0.323	0.174
	(0.084)	(0.086)	(0.115)***	(0.077)**
	(0.031)	(0.045)**	(0.077)***	(0.052)***
Wald test's p-value	[0.961]	[0.208]	[0.007]	[0.027]
	[0.893]	[0.018]	[0.000]	[0.002]

Notes: This table reports results of the growth vs. level regression (10). The first row ("Contemporaneous temp.") reports estimates for coefficient β of the effect of contemporaneous temperature on economic growth, while the second row ("One-year lagged temp.") reports estimates for coefficient β_{lag} of the effects of one-year lagged temperature. The third row ("Sum of coefficients") reports the sum of β and β_{lag}. The last row ("Wald test p-value") reports the p-values, the first clustered by year and the second clustered by state, for the Wald test of whether $\beta + \beta_{lag}$ is significantly different from zero. Temperatures are in degrees Fahrenheit. The sample is 1957–2012. The regressions are weighted by constant GSP shares. Two standard errors, the first clustered by year and the second clustered by state, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

estimated in our main analysis do not change over the time period under consideration, and it ignores the uncertainty about the point-estimates of the coefficients. Equivalently, one can interpret this case as a "business as usual" benchmark, in which there is no adaptation or mitigation, and the effects of temperatures on economic growth in section 3 remain unchanged over the long horizon.

To quantify the potential long-term relevance of the coefficients estimated in section 3, we use two approaches to forecast long-term changes in seasonal temperatures. In the first approach we employ our dataset to estimate the dynamics of the temperature process by means of a simple autoregressive process augmented with a linear time trend. In the interest of space, we report the estimated coefficients in appendix section A.5 and table A4. The results document the clear presence of a positive time trend in average temperatures for all the seasons, and a possibly more robust trend for summer temperatures compared to the other seasons.[6] Focusing on summer and fall (the seasons whose coefficients are statistically significant in table 1), our projections indicate that in 100 years seasonal temperatures will on average be 3.6^{o}F and 2.1^{o}F higher, respectively. This approach should be interpreted with caution, because it extrapolates long-term temperature changes using a short sample.

In the second approach, we employ projections from the climatology literature. The IPCC report by Christensen et al. (2007) calculates the regional averages of seasonal temperature projections from a set of 21 global models in the multimodel dataset (MMD) for the A1B scenario.[7] We focus on the regions in the closest proximity to the U.S. and construct average seasonal projections across those regions. The projected increases in the average summer and fall temperatures that we obtain with this methodology are somewhat more aggressive compared to the linear trend forecasts and are typically around 6^{o}F (see appendix A.5).

There is a clear advantage to using the projections of climatologists, as these forecasts are the outcomes of models that take into account the expected evolution and interaction of demographic, economic, and environmental variables. However, we should also note some of the drawbacks. First, the projections by Christensen et al. (2007) lack a specific projection for the Western part of the country (see appendix figure A1). We mitigate this issue by also considering the projected temperature increases for the regions in close proximity to the U.S. Second, their projections are based on the meteorological definition as opposed to the astronomical definition of seasons that we have adopted in our analysis. Given that the projected increase is quite stable across seasons (the only notable exception being Alaska), we regard this as a relatively minor shortcoming. Third, these forecasts are only available for the A1B scenario, that is, one in which the

[6]This finding is consistent with the analysis of Karl, Melillo and Peterson (2009, 28), who stated: "On a seasonal basis, most of the United States is projected to experience greater warming in summer than in winter."

[7]The A1B scenario describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, the rapid introduction of new and more efficient technologies, and a balance across all energy sources.

variables under consideration are expected to grow very rapidly.

We combine each set of temperature projections with the impact coefficients that we estimated in section 3. Throughout our analysis, we focus on the coefficients for only the summer and the fall seasons, given the lack of statistical significance of the coefficients for winter and spring. We consider two sets of estimates: 1) the one computed on the whole sample ($\hat{\beta}_{summer} = -0.154$, $\hat{\beta}_{fall} = 0.102$), and 2) the one computed on the 1990-onwards sample ($\hat{\beta}_{summer} = -0.254$, $\hat{\beta}_{fall} = 0.031$). In each case, we compute the projected impact on the growth rate of GDP as:

$$E\left[\Delta GDP\right] = \sum_{s \in \{summer, fall\}} E\left[\Delta T_s\right] \times \hat{\beta}_s,$$

where $E\left[\Delta T_s\right]$ and $\hat{\beta}_s$ denote the expected change in the average temperature of season s and the impact coefficient of season s, respectively.

We report the results of our analysis in table 7. The top row ("Whole sample estimates") reports predictions using the coefficients estimated on the full sample. It shows that the projected trend in rising temperatures is expected to reduce the growth rate of U.S. output by 0.2 to 0.4 percentage points over the next 100 years, depending on the specific set of temperature projections being employed. These figures are not negligible: given a historical average growth rate of nominal U.S. GDP of about 4% per year, our first set of estimates implies a possible reduction of up to 10% of the growth rate.

The results are more dramatic when we use estimates obtained from the post-1990 sample (see the row "Post-1990 estimates"). In this case, estimated reductions in output growth due to rising temperatures are between 0.85 and 1.5 percentage points. Thus, assuming no change in the way in which seasonal temperatures affect economic growth, the projected increases in summer and fall temperatures could potentially reduce economic growth by up to 1.5 percentage points, which is more than a third of the historical average nominal U.S. GDP growth rate.

Table 7: Long-term impact of rising temperatures

	Linear Trend	IPCC Projections [1]	[2]	[3]	[4]	[5]
Whole-sample estimates	-0.34	-0.42	-0.27	-0.38	-0.20	-0.24
Post-1990 estimates	-0.85	-1.52	-1.35	-1.50	-1.28	-1.23

Notes: This table reports the projected reduction in the growth rate of GDP over the next 100 years. The row "Whole-sample estimates" uses the estimated coefficients in table 1 ($\hat{\beta}_{summer} = -0.154, \hat{\beta}_{fall} = 0.102$), while the row "Post-1990 estimates" uses the last estimated coefficients of figure 1 ($\hat{\beta}_{summer} = -0.254, \hat{\beta}_{fall} = 0.031$). The figures in the column labeled "Linear Trend" use the projected temperature increases obtained from the estimates in table A4. The numbers in column [1] are obtained by averaging the IPCC projected temperature changes for East US/East Canada, Midwest, and East US; the numbers in column [2] are obtained by averaging the IPCC projected temperature changes for East US/East Canada, Midwest, East US, and Alaska; the numbers in column [3] are obtained by averaging the IPCC projected temperature changes for Midwest and East US; the numbers in column [4] are obtained by averaging the IPCC projected temperature changes for Alaska, Midwest, and East US; the numbers in column [5] are obtained by averaging the IPCC projected temperature changes for all the regions in and around the U.S. (see appendix table A5 for details).

5.3 Robustness checks

In this section we check the robustness of our results to different specifications of main regression (4). The results are reported in table 8. Throughout the table (except the row "Spatial correlation"), we report two standard errors, one clustered by year and one clustered by state, with the corresponding significance levels. Overall, the table shows that the negative relationship between average summer temperature and GSP growth is very robust. We also document that the positive relationship between average fall temperature and growth is not supported in several robustness checks.

The panel labeled "Alternative panel weights" reports the results obtained from using different weighting schemes for the states in the panel regression. Specifically, we weight states by population, area, and time-varying GSP. The last weighting scheme takes into account possible changes over time in the relative distribution of output across states (see appendix A.2.2). The results indicate that the signs of the estimated coefficients are generally aligned with the main findings in section 3.

In the panel labeled "Alternative GSP measures" we report the results obtained by replacing the dependent variable of our regression with per-capita GSP, real GSP, or private industries' GSP. The results of the regressions using these alternative measures of GSP demonstrate that our earlier results are not driven by the growth rate of population, inflation, or the public sector. The alternative measure results also confirm our main finding that an increase in average summer temperature has a strong negative effect on economic growth rates. In some cases, the magnitudes of the estimated summer coefficients are even larger than those obtained in our baseline specification. The effect of the fall season, however, is less robust: an increase in the average fall temperature does not appear to have a significant effect on real GSP growth.

We also check the robustness of our findings to various definitions of seasons (see the panel "Alternative definitions of seasons" in table 8. Specifically, in the row labeled "Meteorological," all seasons are shifted backwards by one month. This means that winter is defined as including December, January, and February; spring is defined as March, April, and May; summer is defined as June, July, and August; and fall is defined as September, October, and November. In the row labeled "Core Seasonal Months," we focus only on the subset of months that fall within both the astronomical and meteorological definitions of a given season. Here, winter is defined as January and February, spring as April and May, summer as July and August, and fall as October and November. The results indicate that the summer effect is generally robust to the various definitions of seasons. When we adopt the meteorological definition, the coefficient on summer temperature is negative, although only statistically significant at the 5% level if standard errors are clustered by state. This may be due to the inclusion of the transitional month of June, during which temperatures have not yet fully adjusted to the seasonal summer average. Indeed, when we only focus on the subset of months that are associated with both the astronomical and meteorological definitions of each season, we get consistently strong results for the summer (see the row "Core Seasonal Months"). This suggests that the economic effect of summer temperatures is mainly driven by the months of July and August. The fall effect, in contrast, is not significant under any of the alternative seasonal definitions.

In the panel labeled "Alternative temperature data" in table 8, we check the robustness of our results to different aggregation methods, deseasonalization methods, and sources of temperature data. As the panel shows, both the summer and fall effects are robust to aggregating station-level weather data to the state level using county population instead of county area (see the row "Temp. weighted by pop.") and to deseasonalizing temperatures using pre-1950 monthly dummies (see the row "Pre-1950 deseasonalization"). Appendix A.2.1 describes method that we use to deseasonalize the temperature data. Furthermore, in the row "Non-deseasonalized gridded temp.," we employ gridded temperature data that is not deseasonalized from the NOAA nClimDiv dataset to show that the deseasonalization of weather data does not drive our results.

In the panel labeled "Other" in table 8 we check the robustness of our results to several additional variations of our main specification. In the row labeled "Spatial correlation," we adjust standard errors to take into account the possible dependence induced by the geographical proximity of the states. Specifically, we employ the correction proposed by Conley (1999) and adapted by Hsiang (2010) to the study of climate-related variables with spatial correlation. We used a radius of 300 km around the center of each state, with a uniform spatial weighting kernel. The ordinary least squares regression is an unweighted state-level panel regression. Our results again show that the summer effect is statistically significant, at the 10% level, but the fall effect is not.

Table 8: Robustness checks

	Winter	Spring	Summer	Fall
Alternative panel weights				
Time-varying GSP	0.008	−0.008	−0.148	0.105
	(0.051)	(0.067)	(0.077)*	(0.058)*
	(0.026)	(0.030)	(0.043)***	(0.042)**
State population	0.028	−0.025	−0.132	0.131
	(0.053)	(0.069)	(0.071)*	(0.061)**
	(0.025)	(0.039)	(0.039)***	(0.043)***
State area	0.018	0.012	−0.098	0.079
	(0.062)	(0.074)	(0.066)	(0.063)
	(0.033)	(0.045)	(0.054)*	(0.064)
Alternative GSP measures				
Per-capita GSP	−0.007	0.018	−0.119	0.098
	(0.047)	(0.068)	(0.071)*	(0.053)*
	(0.025)	(0.033)	(0.049)**	(0.040)**
Real GSP	−0.070	−0.016	−0.194	−0.006
	(0.043)	(0.081)	(0.110)*	(0.068)
	(0.040)*	(0.037)	(0.087)**	(0.053)
Private industries only	0.013	0.010	−0.207	0.115
	(0.063)	(0.083)	(0.087)**	(0.069)*
	(0.029)	(0.041)	(0.060)***	(0.049)**
Alternative definitions of seasons				
Meteorological	0.026	−0.040	−0.083	0.025
	(0.043)	(0.053)	(0.074)	(0.055)
	(0.016)	(0.039)	(0.038)**	(0.033)
Core seasonal months	0.015	−0.026	−0.145	0.036
	(0.041)	(0.050)	(0.066)**	(0.050)
	(0.016)	(0.024)	(0.033)***	(0.027)
Alternative temperature data				
Temp. weighted by pop.	0.012	−0.004	−0.129	0.094
	(0.048)	(0.066)	(0.074)*	(0.057)*
	(0.023)	(0.029)	(0.041)***	(0.034)***
Pre-1950 deseasonalization	0.000	0.003	−0.154	0.102
	(0.049)	(0.065)	(0.072)**	(0.055)*
	(0.025)	(0.032)	(0.047)***	(0.040)**
Non-deseasonalized gridded temp.	0.001	−0.005	−0.167	0.100
	(0.042)	(0.057)	(0.064)***	(0.047)**
	(0.023)	(0.028)	(0.047)***	(0.035)***

↪ Continued on Next Page

Table 8: Robustness checks (continued)

	Winter	**Spring**	**Summer**	**Fall**
Other				
Spatial correlation	0.011	−0.020	−0.109	0.024
	(0.046)	(0.061)	(0.066)*	(0.058)
Controlling for precipitation	0.003	0.008	−0.169	0.093
	(0.047)	(0.069)	(0.077)**	(0.056)*
	(0.025)	(0.039)	(0.048)***	(0.037)**
Controlling for temp. vol.	−0.009	−0.013	−0.138	0.106
	(0.050)	(0.062)	(0.071)*	(0.055)*
	(0.024)	(0.030)	(0.042)***	(0.040)***
Excluding AR(1)	0.023	0.014	−0.156	0.086
	(0.052)	(0.073)	(0.080)*	(0.059)
	(0.029)	(0.039)	(0.054)***	(0.036)**
Excluding Alaska and Hawaii	−0.001	0.000	−0.153	0.118
	(0.048)	(0.065)	(0.071)**	(0.056)**
	(0.026)	(0.032)	(0.048)***	(0.040)***

Notes: This table reports robustness checks for main regression (4). Temperatures are in degrees Fahrenheit. The sample is 1957–2012, except for the row with private industries only, in which the sample is 1963–2011, and the row with real GSP, in which the sample is 1987–2012. In all regressions except those in "Alternative panel weights" and "Spatial correlation," each state is weighted by the proportion, averaged over the whole sample, of its GSP relative to the whole country's GDP. In "Time-varying GSP," each state in each year is weighted by the proportion of its GSP relative to the whole country's GDP in that year. In "State population" and "State area," each state is weighted by the proportion, averaged over the whole sample, of its population or area, respectively. In the row "Core seasonal months," winter is Jan.–Feb., spring is Apr.–May., summer is Jul.–Aug., fall is Nov.–Dec. In the row "Spatial correlation", all states are equally weighted. The first number in parentheses below each estimated parameter is the standard error clustered by year, while the second number is the standard error clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

We also include average precipitation (the row "Controlling for precipitation") and temperature volatility (the row "Controlling for temp. vol.") in our main specification. The temperature volatility of season s in year t is calculated as the standard deviation of the deseasonalized temperature observations in that season (see appendix A.2.1 for details on deseasonalization). We find that controlling for these two additional sets of control variables does not alter our main conclusions regarding the effect of summer and fall temperatures on GSP growth.

Our results are robust to the exclusion of the lagged growth rate of GSP. This finding is important in light of the so-called Nickell (1981) bias, which arises in the context of dynamic panel models with fixed effects in a short sample. The results shown in row "Excluding AR(1)" of table 8 are from panel regressions that do not included lagged GSP. As shown, the negative effect of summer temperature is still economically and statistically significant. We also note that the magnitudes of the estimated coefficients are very close to the ones obtained in table 1, which can be interpreted as evidence for a small overall impact of the bias on our results. In related studies, Judson and Owen (1999), Acemoglu et al. (2014), and Deryugina and Hsiang (2014) reach similar conclusions regarding the extent of the bias.

Finally, the row labeled "Excluding Alaska and Hawaii" shows that our results are robust to excluding the two non-contiguous states of Alaska and Hawaii. In summary, the battery of tests using various alternative specifications has shown that the effect of summer temperatures is generally very robust, but that of fall temperatures generally less so.

6 Conclusion

In this paper, we analyze the effects of increases in average seasonal temperatures on economic growth across U.S. states. We find that an increase in the average summer temperature has a significant and robust negative effect on GSP growth. We also find a positive, albeit weaker and less robust, effect of an increase in the average fall temperature. In net, the summer effect dominates, and the total impact of increases in seasonal temperatures is substantial: under the business-as-usual scenario, the projected trends in rising temperatures could depress U.S. economic growth by up to a third.

Our results are informative for the calibration of the climate damage functions in general equilibrium models, and they should be helpful as well in advancing the analysis of the long-term effects of climate change (e.g., Stern (2007), Nordhaus and Sztorc (2013), Bansal and Ochoa (2011), and Giglio et al. (2015)). These results highlight the importance of building the next generation of equilibrium models for the environment that take into account the heterogeneous effect that rising temperatures have on the cross-section of industries and explictly modeling the effects of seasonal temperatures on labor productivity and other economic variables.

Finally, the finding that the effect of summer temperatures is stronger in the states that are on average warmer than the rest of the country is related to the nonlinear effects of rising temperatures in the studies of Schlenker and Roberts (2006; 2009) and Burke, Hsiang and Miguel (2015). Future research should employ methodologies from these studies to further investigate potential nonlinearities in the effects of seasonal temperatures on the cross-section of industries.

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Online Appendix

A.1 Weather Stations

We use weather data from 129 weather areas featuring a total of 10,128 individual weather stations, with the number of weather stations per area ranging from 2 to 295. The data for a weather area are created by collecting the earliest available data from a currently active weather station in that area. The data series is then extended further by using another weather station in the area.[1] For example, the weather data series for the Nashville, TN area is compiled from three individual weather stations over the time period 1871–2014.[2]

Using data for weather areas, as opposed to individual weather stations, avoids the problem of missing daily data without sacrificing a significant amount of temperature information because the correlation of average temperature reported across stations in a given area is very high. For example, table A1 shows the correlation between daily average temperatures reported by individual stations in the Nashville area and in the Las Vegas area. Individual stations are included in the table if they report at least 60 daily observations per season for each season in the sample 1957–2012. There are 54 stations in the Nashville area and 8 meet the inclusion criteria, and there are 83 stations in the Las Vegas area and 7 meet the inclusion criteria. The correlations in daily temperature reported across stations are greater than 0.99.

Next, we calculate the correlation between individual stations in each area over the 20-year period with the greatest number of individual stations meeting the inclusion criteria of 60 daily observations per season. Twenty-year periods beginning in 1959–1962 have the greatest number of stations meeting the inclusion criteria for Nashville

[1] http://threadex.rcc-acis.org/

[2] http://threadex.rcc-acis.org/threadex/process_records

and the 20-year period beginning in 1969 has the greatest number of stations meeting the inclusion criteria for Las Vegas. This increases the number of individual stations to 21 for Nashville and to 16 for Las Vegas. For the 20-year period beginning in 1959, the minimum correlation between any two stations in Nashville is 0.9882, and for the 20-year period beginning in 1969, the minimum correlation between any two stations in Las Vegas is 0.9785.

Finally, in order to consider all stations in each area, we impute missing seasonal data for individual stations that report any daily data in 1957–2012. This includes 53 of 54 weather stations in Nashville and 78 of 83 weather stations in Las Vegas. Specifically, we consider the seasonal average for a station to be missing if the station does not report at least 60 daily observations in that season. We replace missing seasonal data with the mean of the seasonal average of all stations. The mean correlation between stations in Nashville is 0.9959 and the mean correlation between stations in Las Vegas is 0.9463.

Table A1: Correlation of Individual Stations a Weather Area

	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8
Panel A: OHX: Nashville, TN								
Station 1	1.0000							
Station 2	0.9971	1.0000						
Station 3	0.9984	0.9973	1.0000					
Station 4	0.9977	0.9982	0.9983	1.0000				
Station 5	0.9968	0.9937	0.9976	0.9955	1.0000			
Station 6	0.9977	0.9980	0.9983	0.9983	0.9957	1.0000		
Station 7	0.9977	0.9980	0.9983	0.9983	0.9957	1.0000	1.0000	
Station 8	0.9978	0.9969	0.9979	0.9976	0.9965	0.9979	0.9979	1.0000
Panel B: VEF: Las Vegas, NV								
Station 1	1.0000							
Station 2	0.9948	1.0000						
Station 3	0.9948	1.0000	1.0000					
Station 4	0.9935	0.9928	0.9928	1.0000				
Station 5	0.9935	0.9928	0.9928	1.0000	1.0000			
Station 6	0.9952	0.9944	0.9944	0.9979	0.9979	1.0000		
Station 7	0.9956	0.9968	0.9968	0.9956	0.9956	0.9964	1.0000	

Notes: Individual stations are included in the table if they have at least 60 daily observations per season for each season in the sample (1957–2012).

A.2 Additional details of the empirical analysis

A.2.1 Deseasonalization

We regress each raw temperature observation $T_{j,\tau}$ at station j and day τ using the following specification:

$$T_{j,\tau} = \sum_{m=1}^{12} \gamma_m I_{j,m} + \alpha_j + \varepsilon_\tau,$$

where $I_{j,m}$ is a dummy for month m at station j, α_j is a station fixed effect, and ϵ_τ is an error term. Then the deseasonalized station observation is

$$\tilde{T}_{j,\tau} \equiv T_{j,\tau} - (\sum_{m=1}^{12} \hat{\gamma}_m I_{j,m} + \hat{\alpha}_j).$$

In the row labeled "Pre-1950 deseasonalization" in table 8, we estimate γ_m and α_j using weather data up to only 1950.

A.2.2 GSP weights

In panel regressions using constant GSP weights, state i's weight is calculated as the proportion of state i's total GSP over the sample 1957–2012 relative to national GDP (the total of all states' GSP) over the sample 1957–2012. Specifically, let $g_{i,1}, \ldots, g_{i,T}$ denote state i's GSP in year $t = 1, \ldots, T$; then the weight of state i in the main specification in the panel regression (section 3) is $\frac{\sum_{t=1}^{T} g_{i,t}}{\sum_{t=1}^{T} \sum_{i=1}^{51} g_{i,t}}$. In this way, the weight of each state in the regression is time invariant.

In the "Time-varying GSP" row of table 8, we use time-varying GSP weights instead of constant GSP weights. In this panel regression, each state i in year t is weighted by the proportion of state i's GSP in year t relative to national GDP in year t. Specifically, the weight of state i in year t is $\frac{g_{i,t}}{\sum_{i=1}^{51} g_{i,t}}$.

A.3 Industry group classification

Table A2 provides the classifications of the industry groups used in the industry analysis in section 4.2, with industry output data and classifications from the Bureau of Economic Analysis. The column "Pre-1997 classification" uses the industry group categories of the Standard Industrial Classification (SIC). The column "Post-1997 classification" uses the industry group categories of the North American Industry Classification System (NAICS).

A.4 Definitions of U.S. regions and Ranking of States

We follow the U.S. Census Bureau and identify four geographic regions:

1. North: Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont;

2. Midwest: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin;

3. South: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington D.C., and West Virginia;

4. West: Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah,Washington, and Wyoming.

Table A2: Industry Classifications

Industry group	Pre-1997 classification (SIC)	Post-1997 classification (NAICS)
Services	Services	Professional, scientific, technical services
		Management of companies and enterprises
		Administrative, waste management services
		Educational services
		Health care and social assistance
		Arts, entertainment, and recreation
		Accommodation and food services
		Other services, except government
Finance, insurance, real estate	Finance, insurance, real estate	Finance and insurance
		Real estate and rental and leasing
Manufacturing	Manufacturing	Manufacturing
Government	Government	Government
Retail	Retail trade	Retail trade
Wholesale	Wholesale trade	Wholesale trade
Communication/Information	Communications	Publishing industries, except Internet
	Printing and publishing	Motion picture, sound recording industries
	Motion pictures	Broadcasting and telecommunications
		Information and data processing services
Construction	Construction	Construction
Transportation	Transportation	Transportation and warehousing
Utilities	Electric, gas, sanitary services	Utilities
Mining	Mining	Mining
Agriculture, forestry, fishing	Agriculture, forestry, fishing	Agriculture, forestry, fishing, and hunting

Notes: Definitions from the Bureau of Economic Analysis.

Table A3: State Ranking by Average Summer Temperature

Rank	State	Avg. Summer Temp	Rank	State	Avg. Summer Temp
1	Florida	80.78	26	Iowa	69.13
2	Louisiana	80.18	27	West Virginia	68.88
3	Texas	79.87	28	Nevada	68.61
4	Mississippi	78.44	29	South Dakota	68.02
5	Oklahoma	78.21	30	Rhode Island	67.92
6	Alabama	77.67	31	Utah	67.85
7	Georgia	77.64	32	Connecticut	67.61
8	South Carolina	77.47	33	Pennsylvania	67.03
9	Arkansas	77.20	34	Massachusetts	66.59
10	Arizona	77.06	35	New York	64.70
11	Kansas	74.70	36	Wisconsin	64.64
12	North Carolina	74.30	37	Michigan	64.54
13	Tennessee	74.21	38	North Dakota	64.44
14	Missouri	73.65	39	Minnesota	64.32
15	California	73.07	40	Colorado	63.67
16	Kentucky	72.92	41	New Hampshire	62.95
17	Delaware	72.89	42	Oregon	62.77
18	Maryland	72.32	43	Vermont	62.25
19	Virginia	71.84	44	Washington	62.07
20	Illinois	71.58	45	Montana	61.72
21	New Jersey	70.87	46	Maine	61.66
22	Indiana	70.64	47	Idaho	61.62
23	Nebraska	69.80	48	Wyoming	61.25
24	New Mexico	69.63	49	Alaska	47.97
25	Ohio	69.45			

Notes: Hawaii and the District of Columbia are not included. Summer is defined as July, August, and September. Average summer temperature is calculated over the sample 1957–2012. Monthly temperature data are from NOAA.

Table A3 displays each state' ranking by average summer temperature and the average summer temperature used to determine this rank. This ranking is used to determine the samples for the results presented in figure 2.

A.5 Temperature projections in section 5.2

Linear projections. We use a simple autoregressive process augmented with a linear time trend to assess the projected growth rate of temperature over the next 100 years. We specify the process as:

$$T_{i,t} = \mu_T^i + \rho_T^i T_{i,t-1} + \beta_i \cdot t + \sigma_T^i \varepsilon_{w,t}^i, \tag{A1}$$

Table A4: Dynamics of Average Temperature (1960–2012)

		Whole Year	Winter	Spring	Summer	Fall
Country	Trend	0.041***	0.071***	0.034***	0.036***	0.021**
		(0.006)	(0.015)	(0.010)	(0.008)	(0.009)
	AR(1)	0.077	−0.048	0.143	0.061	−0.212
		(0.149)	(0.146)	(0.143)	(0.141)	(0.139)
North	Trend	0.048***	0.080***	0.041***	0.035***	0.036***
		(0.008)	(0.023)	(0.011)	(0.009)	(0.012)
	AR(1)	0.047	0.147	−0.000	−0.184	−0.328**
		(0.143)	(0.149)	(0.138)	(0.132)	(0.133)
South	Trend	0.040***	0.075***	0.033***	0.031***	0.019**
		(0.008)	(0.022)	(0.012)	(0.009)	(0.009)
	AR(1)	0.160	0.200	0.070	−0.047	−0.359***
		(0.151)	(0.146)	(0.145)	(0.140)	(0.132)
Midwest	Trend	0.042***	0.088***	0.028*	0.031***	0.017
		(0.011)	(0.027)	(0.016)	(0.011)	(0.013)
	AR(1)	0.185	0.072	0.158	0.017	−0.247*
		(0.149)	(0.148)	(0.144)	(0.141)	(0.137)
West	Trend	0.040***	0.064***	0.035***	0.040***	0.020
		(0.007)	(0.012)	(0.013)	(0.008)	(0.013)
	AR(1)	0.001	−0.271**	0.126	−0.024	0.003
		(0.143)	(0.136)	(0.141)	(0.143)	(0.142)

Notes: This table reports the estimates of the autoregressive coefficient and of the time trend for temperature. The column "Whole Year" refers to the annual temperature estimation, while the columns "Winter," "Spring," "Summer," and "Fall" refer to the corresponding season. The row "Country" reports the estimates obtained using national aggregate temperature data, while the subsequent rows refer to the corresponding regions. All the regressions also include an intercept, which is not reported in the interest of space. The sample is 1960–2012.

where i indexes the four seasons. For consistency with the estimations reported in the main text, we focus on the 1960–2012 sample period. The results of this estimation, reported in Table A4, document the clear presence of a positive time trend in average temperatures for all seasons, and a possibly more robust trend for summer temperatures compared to the other seasons. Ignoring the AR(1) coefficients (which are not statistically significant at the whole-country level), the first panel of table A4 suggests that in 100 years the average summer and fall temperatures will be $0.0036 \times 100 = 3.6^o$F and $0.021 \times 100 = 2.1^o$F higher, respectively.

Climatologists' projections. The projections are obtained from Christensen et al. (2007), who report projections over the next century for temperature and precipitation changes. In their procedure, the mean temperature and precipitation responses are first averaged for each model over all available realizations of the 1980–1999 period from the 20th Century Climate in Coupled Models (20C3M) simulations and the 2080–2099 period of A1B. The A1 storyline and scenario family describe a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), nonfossil energy sources (A1T), or a balance across all sources (A1B).

In figure A1, we show the map of the regions we used to form projections for the entire U.S. based on the regional projections provided by Christensen et al. (2007).

In table A5, we report the details of the projections used for the analysis of section 5.2 of main text. Panel A documents the raw projections of Christensen et al. (2007). The column denoted "Abbr." corresponds to the abbreviation used by Christensen et al. (2007); the column "Approx. area" is our approximate description of the associated area; the column "Coordinates" provides the geographical coordinates of each area as in Christensen et al. (2007), with the exception of the "WNA" area in which we replaced "50E" with "50W"; and the column "Surface" provides the area of each region in square miles obtained from Google maps. The last four columns report the projections of Christensen et al. (2007) for each season, defined according to the meteorological convention. Panel B reports the seasonal projections associated with averaging the projections for the corresponding combinations of areas. Averages are either equally weighted across regions (denoted as "Equal" in the "Weighting" column) or weighted in proportion to their surface area (denoted as "Area" in the "Weighting" column).

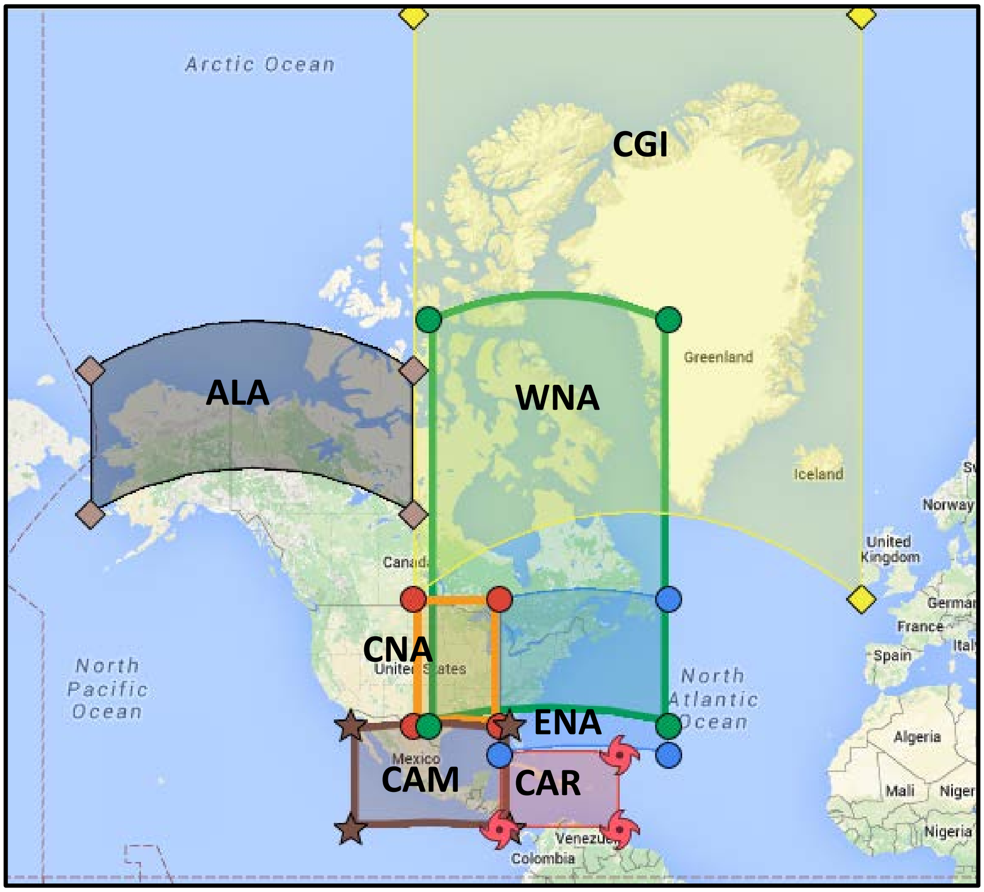

Figure A1: Geographical areas for IPCC temperature projections

Notes - This figure provides the geographical areas for which Christensen et al. (2007) provided a projection for the temperature change over the next 100 years. For the exact coordinates of each area refer to Table A5.

Table A5: IPCC projections

Panel A: Area projections

Abbr.	**Approx. area**	**Coordinates**	**Surface**	**Win.**	**Spr.**	**Sum.**	**Fall**
ALA	Alaska	60N,170W to 72N,103W	1298469	11.34	6.30	4.32	8.10
CGI	Canada, Greenland	50N,103W to 85N,10W	4100546	10.62	6.84	5.04	7.20
WNA	East US, Canada	30N,50W to 75N,100W	6098707	6.48	5.58	6.84	5.58
CNA	Midwest	30N,103W to 50N,85W	1310340	6.30	5.94	7.38	6.30
ENA	East US	25N,85W to 50N,50W	3283483	6.84	6.30	5.94	6.30
CAM	Central America	10N,116W to 30N, 83W	3004622	4.68	6.48	6.12	5.76
CAR	Caribbean	10N,85W to 25N,60W	1725932	3.78	3.96	3.60	3.60

Panel B: Country aggregate projections

	Weighting	**Winter**	**Spring**	**Summer**	**Fall**
WNA+CNA+ENA	Equal	6.54	5.94	6.72	6.06
WNA+CNA+ENA+ALA	Equal	7.74	6.03	6.12	6.57
CNA+ENA	Equal	6.57	6.12	6.66	6.30
CNA+ENA+ALA	Equal	8.16	6.18	5.88	6.90
All	Equal	7.15	5.91	5.61	6.12
WNA+CNA+ENA	Area	6.57	5.85	6.63	5.89
WNA+CNA+ENA+ALA	Area	7.09	5.89	6.38	6.13
CNA+ENA	Area	6.69	6.20	6.35	6.30
CNA+ENA+ALA	Area	7.71	6.22	5.90	6.70
All	Area	7.16	6.00	5.85	6.08

Notes: Panel A reports the projections of regional temperature increases by Christensen et al. (2007). The column "Abbr." denotes the abbreviations used by Christensen et al. (2007); the column "Approx. area" denotes the approximate geographical area associated with each regional forecast; the column "Coordinates" denotes the geographical coordinates of each area; the column "Surface" denotes the surface of the area in square miles; the columns "Winter," "Spring," "Summer," and "Fall" denote the projected temperature increases over the next 100 years in degrees Fahrenheit. Panel B reports the projections aggregated to the country level. The first column reports the areas that are being aggregated; the column "Weighting" reports whether the areas are equally or area weighted; the right-most four columns report the forecasted seasonal temperature changes over the next 100 years for each season. Seasons are defined according to the meteorological convention.