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Temperature and Growth: A Panel Analysis of the United States

We document 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: 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. We combine our estimates with projected increases in seasonal temperatures and find that rising temperatures could reduce U.S. economic growth by up to one-third over the next century.

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WE ANALYZE THE EFFECT OF average seasonal temperatures on the growth rate of U.S. output. We find that seasonal temperatures, particularly

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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 0.15–0.25 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, 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, Burke and Emerick 2016, for analyses of the 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 state gross domestic product (GDP), or gross state product (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, Jones, and Olken 2012) may mask the heterogenous 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, Deschenes, and Guldi 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. However, we do not find any evidence that the effect of temperature on GDP in the South is driven by the relatively less developed states. This implies that the channel through which temperature affects GDP in this part of the country must be distinct from the one documented in the literature for developing economies.

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. Figure 1 documents that, in the most recent part of our sample, an increase in the average summer temperature negatively affects the growth rate of output of many industries,

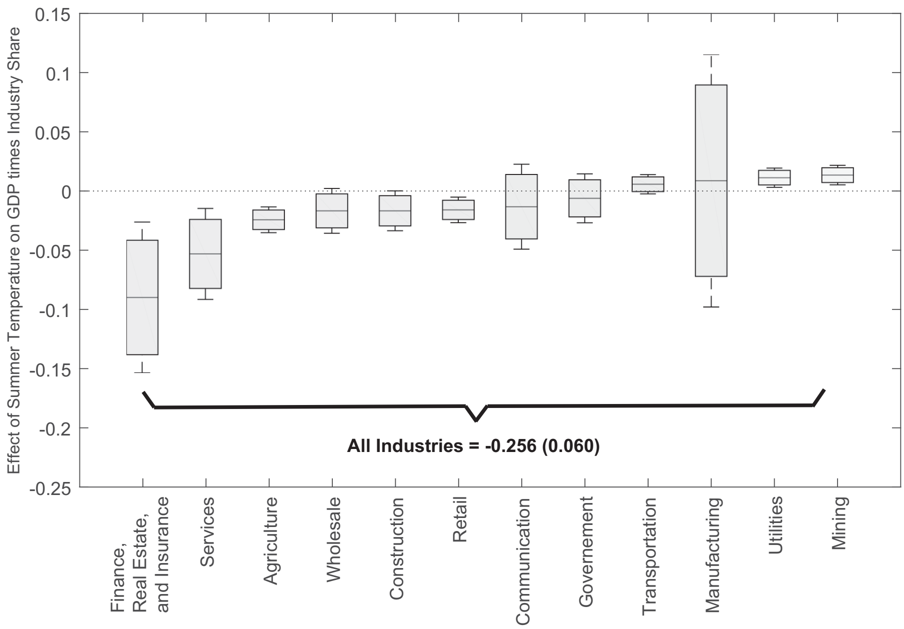

FIG. 1. Decomposition of the Summer Temperature Effect in the Cross Section of Industries.

NOTE: For each industry, the horizontal line represents the point estimate of the impact of summer temperature on the growth rate of industry GDP times the industry share of GDP. The bottom and top portions of each rectangle represent 90% confidence intervals, while the outer limits of each boxplot represent the 95% confidence interval of each estimated coefficient. Standard errors are clustered at the year level. The number denoted as "All Industries" is the sum of all the industry coefficients multiplied by the corresponding industry share. All estimates refer to the post-1997 sample as documented in Table 4.

including finance, services, retail, wholesale, and construction, which in total account for more than a third of national GDP. 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.[1] To the best of our knowledge, our paper is the first in the literature to systematically document the pervasive effect of summer temperatures on the cross section of industries in the U.S.

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) have documented that high temperatures decrease productivity and performance.

1. Section 3.2 provides a comprehensive breakdown of these results across different samples and subindustries.

Our paper also contributes to the growing debate on the long-term economic consequences of rising global temperatures (e.g., Mendelsohn and Neumann 1999, 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 1.2 percentage points, which is roughly 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 of 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., Bansal and Ochoa 2011, Acemoglu et al. 2012, Bansal, Ochoa, and Kiku 2014, Golosov et al. 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 focus on quarterly temperature fluctuations allows us to combine our estimates with existing climatological projections, which are typically only available at lower frequencies. Our analysis differs from a large literature that uses daily temperature fluctuations to study outcomes as diverse as agriculture, local income, birth weight, mortality, and time allocation (Schlenker and Roberts 2006, Deschênes and Greenstone 2007, Deschênes, Greenstone, and Guryan 2009, Deschênes and Greenstone 2011, Deryugina and Hsiang 2014, Zivin and Neidell 2014). Although studies using high-frequency data typically focus on the effect of a change in the observed distribution of daily temperature, we focus on the effect of a change in the mean seasonal temperature.

In a similar vein, 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 1 provides a description of the main data sets that we employ in our analysis. Section 2 describes our main results and documents the stability of the estimated effects over time. Section 3 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 4 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 5 concludes. The Appendix provides a comprehensive set of robustness exercises.

1. 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.

1.1 Weather Data

We use daily station-level weather data from the National Oceanic and Atmospheric Administration (NOAA) Northeast Regional Climate Center. This data set 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 section "Deseasonalization" in the Appendix for details on deseasonalization).[2]

We aggregate daily weather observations to quarterly averages by taking the average of the daily observations in each season. 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 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. We also consider alternative definitions of seasons in the robustness checks in Section 4.3.

2. We have followed the common practice in the macroeconomics literature of not correcting the standard errors of our analysis to account for the deseasonalization. However, we provide a robustness check of our results using a data set that does not seasonally adjust temperatures.

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 4.3 and section "Temperature aggregated by population data" in the Appendix). We aggregate state-level weather data to the country level by following the same procedure.

In Section 4.3, we document that our results are robust to using nondeseasonalized gridded temperature data. We use the NOAA U.S. Climate Divisions' nClimDiv data set, which provides absolute monthly temperature averages for each state, derived from area-weighted averages of 5 km $\times$ 5 km grid-point temperature estimates interpolated from station data.[3] In section "Gridded temperature data set" of the Appendix, we replicate all of our results by using gridded temperature data from the NOAA nClimDiv data set. We show that our results are robust to the use of this alternative data set.

1.2 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. See ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/climdiv-inv-readme.txt for more details.

2. 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 existing 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").

For the baseline specifications that we consider, we always include the lagged dependent variable and the average seasonal temperatures. We motivate the inclusion of lagged GDP growth rates with the strong empirical evidence supporting the claim of first-order autocorrelation of this variable in the cross section of U.S. states (see Table A5 for a complete set of estimates).[4] Furthermore, we document in Table A6 that the correlation of seasonal temperatures is typically very low. This supports the claim that our results are unlikely to be affected by multicollinearity.

Our main findings are as follows: (i) an increase in the average summer temperature negatively affects the growth rate of GSP, and (ii) an increase in the average fall temperature positively affects growth, although to a lesser extent. Both effects are statistically and economically significant. In Section 4.3, 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.

Our finding on the compositional effect of seasonal temperatures on GDP is relevant because it implies that temperature fluctuations may also affect the volatility of GDP growth. Indeed, given the modest degree of correlation of seasonal temperatures (see Table A6), our results indicate that temperature's volatility will contribute to GDP volatility. This is an important result in light of an abundant macroliterature on the welfare costs of economic fluctuations. This literature, which was started by Lucas (1987), is interested in the question of how much would economic agents be willing to pay in order to eliminate all sources of fluctuations in business cycles. Equivalently, if temperature does contribute to business cycle fluctuations, then our analysis is relevant because it points out that there are welfare consequences associated with large temperature variations.

2.1 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:

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

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 Fahrenheit; and the lagged growth rate Δy_{t-1} controls for autocorrelation.

4. A common concern about including lagged dependent variables in our regressions is that this could give rise to the Nickell (1981) bias. We show in Section 4.3 that our results are robust to excluding the lagged dependent variable.

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)***
	(0.105)	(0.044)	(0.051)	(0.065)**	(0.054)*

NOTE: 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 standard errors are clustered by year, by state, and by both dimensions. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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

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

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.

2.2 *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. We show in section "Arellano–Bond estimator" of the Appendix that our results are robust to using the Arellano and Bond (1991) estimation methodology.

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 section "GSP weights" of the Appendix for details). In Section 4.3, 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. 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_s seasonal coefficients with associated standard errors, clustered by year, by state, and in both dimensions. 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°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°F increase in the average fall temperature is associated with an increase in the annual GSP growth rate by 0.102 percentage points.[5]

The opposite signs of the effects 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 4.3) and the exercise below that the summer effect is much more robust than the fall effect.

2.3 *Growth versus Level Effects*

We test whether the response of GSP to temperature in the previous section 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, Jones, and Olken 2012).

5. We note that the time-series point estimates for the summer are larger than the corresponding panel coefficients, but they are statistically insignificant. This means that by using state-level data, we obtain an increase in precision due to the increased ability to connect temperatures to local economic variables.

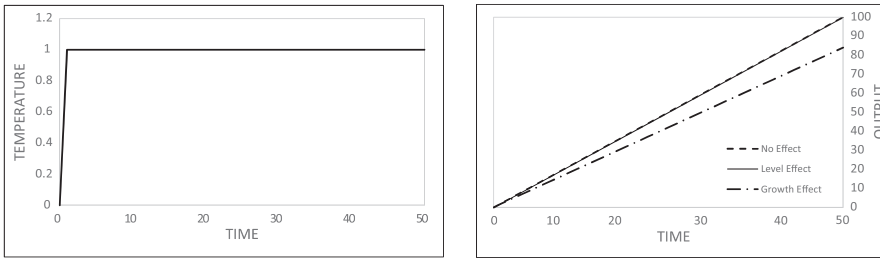

FIG. 2. Growth versus Level Effect.

NOTE: The left panel depicts a permanent increase of 1°F 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 (5), by setting $\beta = \beta_{\text{lag}} = 0$ (dashed line), $\beta = -\beta_{\text{lag}} = -0.170$ (solid line), and $\beta = -0.170$, $\beta_{\text{lag}} = -0.153$ (dash–dot line). In all three cases, $\alpha = 2$ and $\varepsilon_t = 0, \forall t$.

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:

$$y_t = \alpha + y_{t-1} + \beta T_t + \beta_{\text{lag}} T_{t-1} + \varepsilon_t, \tag{5}$$

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 1°F, from $T_0 = 0$ to $T_t = 1, \forall t \geq 1$ (illustrated in the left panel of Figure 2). This temperature path is motivated by climatologists' predictions that temperatures will rise permanently by the middle and end of this century (see Section 4.2 for details). Along this hypothetical temperature path, the level and the growth rate of output would be

$$y_t = (y_0 + \beta) + (t-1)\left[\alpha + \left(\beta + \beta_{\text{lag}}\right)\right], \text{ and} \tag{6}$$

$$\Delta y_1 = \alpha + \beta, \qquad \text{and} \qquad \Delta y_t = \alpha + \left(\beta + \beta_{\text{lag}}\right), \quad \forall t \geq 2, \tag{7}$$

respectively. We consider three cases. If $\beta = \beta_{\text{lag}} = 0$, then temperatures have no economic effect. We refer to this situation as the No Effect case. If $\beta + \beta_{\text{lag}} = 0$, then an increase in temperature has a permanent impact on the level of output (see equation (6)), but it affects the growth rate of output for only one period (see equation (7)). We refer to this situation as the Level Effect case. If $\beta + \beta_{\text{lag}} \neq 0$, 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 2. Over the span of 50 years, if temperatures permanently affect the growth rate of output (the Growth

TABLE 2

Growth versus Level Effects

	Winter	Spring	Summer	Fall
Contemporaneous temp.	−0.008	−0.012	−0.170	0.108
	(0.051)	(0.059)	(0.076)**	(0.050)**
	(0.029)	(0.032)	(0.045)***	(0.038)***
	(0.048)	(0.046)	(0.067)**	(0.048)**
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)**
	(0.046)	(0.054)**	(0.075)**	(0.049)
Sum of coefficients	−0.004	0.109	−0.323	0.174
	(0.084)	(0.086)	(0.115)***	(0.077)**
	(0.031)	(0.045)**	(0.077)***	(0.052)***
	(0.075)	(0.068)	(0.108)***	(0.067)***
Wald test's p-value	[0.961]	[0.208]	[0.007]	[0.027]
	[0.893]	[0.018]	[0.000]	[0.002]
	[0.956]	[0.110]	[0.003]	[0.009]

Note: This table reports results of the growth versus level regression (8). 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 1-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 for the Wald test of whether $\beta + \beta_{\text{lag}}$ is significantly different from zero. Temperatures are in degrees Fahrenheit. The sample is 1957–2012. The regressions are weighted by constant GSP shares. The standard errors, clustered by year, by state, and by both dimensions, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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:

$$\Delta y_{i,t} = \sum_{s\in\mathcal{S}} \beta_s T_{i,s,t} + \underbrace{\sum_{s\in\mathcal{S}} \beta_{\text{lag},s} T_{i,s,t-1}}_{\text{lagged terms}} + \rho \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \tag{8}$$

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, $H_0 : \beta_s + \beta_{\text{lag},s} = 0$, for each season s.[6]

Our results, reported in Table 2, 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.

6. Note that by setting $\beta_s \equiv \beta/4$, $\beta_{\text{lag},s} \equiv \beta_{\text{lag}}/4$, 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.

Most importantly, from the p-values of the Wald tests reported on the last row of the table, we can strongly reject the null hypothesis that the sums of the contemporaneous and lagged temperature coefficients are equal to zero ($\beta_s + \beta_{\text{lag},s} = 0$) for summer and fall. This evidence supports the hypothesis that increases in summer and fall temperatures have lasting effects on output growth. Table A4 provides several robustness checks for the result reported in Table 2.

In what follows, we will focus primarily on an econometric specification that omits lagged temperatures for parsimony. While this results in a bias in our estimated coefficients, we note that such bias affects primarily the estimate of the autoregressive coefficient, and only marginally the estimated temperature coefficients (as can be noted by comparing Tables 1 and 2). For completeness, the robustness of all the results of our subsequent analysis including lagged temperatures are reported in section "Including one-year lagged temperatures" of the Appendix.

2.4 Stability of the Effects through Time

We explore how the estimated coefficients in the main 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 (e.g., due to widespread adoption of air conditioning technologies as documented by Barreca, Deschenes, and Guldi 2015).

We rerun the regression specified in equation (4) but delay the beginning of the sample by 1 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 power of our estimation. The results, reported in Figure 3, 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 -0.246 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 and 0.031 (and indistinguishable from zero) in the post-1990 sample. This finding is consistent with the results of our robustness checks (Section 4.3): the summer effect is very robust, but the fall effect is not.

3. 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.

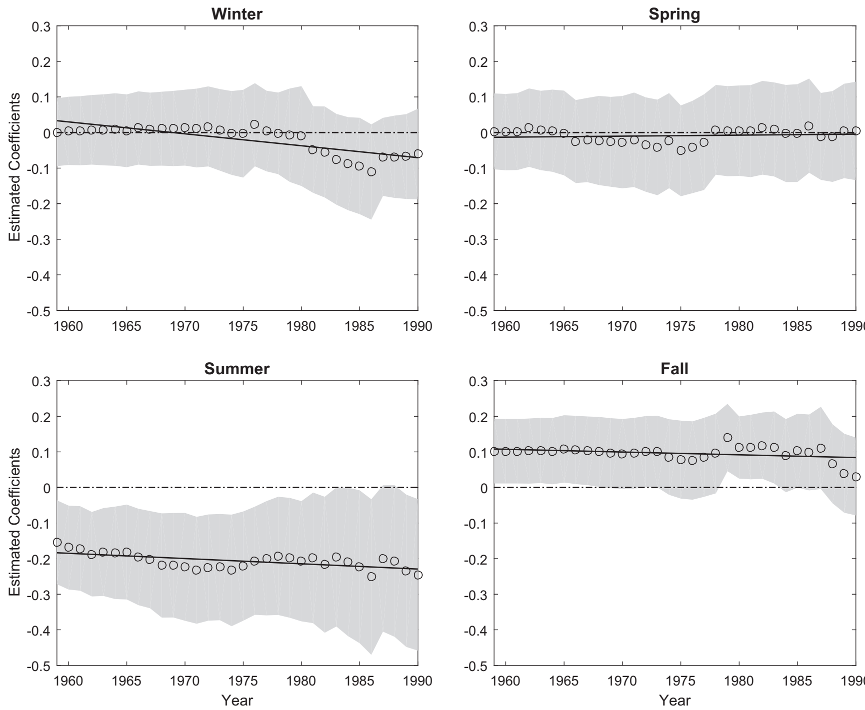

Fig. 3. Stability across Time of the Effect of Average Seasonal Temperatures on GSP Growth.

Note: 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 gray 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.

3.1 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 4.3) 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.[7]

7. Garofalo and Yamarik (2002) built a data set 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.

TABLE 3

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)***
	(0.041)	(0.031)	(0.049)***	(0.054)**
	(0.055)	(0.028)	(0.063)**	(0.039)***
Employment	0.013	−0.086	0.008	−0.021
	(0.032)	(0.051)*	(0.059)	(0.041)
	(0.015)	(0.051)*	(0.037)	(0.019)
	(0.024)	(0.055)	(0.049)	(0.032)

NOTE: 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 January–March, spring as April–June, summer as July–September, fall as October–December. Temperatures are in degrees Fahrenheit. The sample is 1990–2011. The standard errors, clustered by year, by state, and by both dimensions, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

In the top panel of Table 3, we report the results of our analysis of the growth rate of annual labor productivity. Specifically, we estimate the coefficients of the following specification:

$$\Delta a_{i,t} = \sum_{s \in \mathcal{S}} \beta_s T_{i,s,t} + \rho \Delta a_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{9}$$

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 (9) 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 3 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 3 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 3 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, Gallino, and Olivares (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°F reduces the weekly production of U.S. automobile manufacturing plants by an average of 8%. Given that automobile manufacturing largely takes place indoors, the authors argue that this finding suggests that there are limitations of air conditioning; it is possible that there are important areas in the production process, such as loading and unloading areas, which are difficult to cool or warm. Bloesch and Gourio (2015) also document that cold weather negatively affects production in various industries. We will 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, Fisk, and Lei-Gomez (2006) document that performance at office tasks decreases at high temperatures. Similarly, Adhvaryu, Kala, and Nyshadham (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, Hsiang, and Neidell (2015) study the effect of short-run weather shocks on cognitive performance and find that an increase in outdoor temperature decreases math performance.

3.2 Industry Analysis

A common perception is that the effects of global warming are limited to agriculture-related sectors, which constitute a relatively small fraction of GDP in developed countries. In this section, we revisit this idea and explore the composition of the effects documented in the panel regressions of Table 1. Our analysis is guided by existing microlevel evidence of possible mechanisms through which temperature may affect economic activities.

First, high temperatures negatively affect the productivity of workers, especially in what Cachon, Gallino, and Olivares (2012) call interface areas, such as loading and unloading areas, which are difficult to cool with air conditioning. This constitutes a potential pathway through which high temperatures may affect sectors such as *retail*, *wholesale*, and *construction*.

Second, the fact that high temperatures exert a negative impact on health is well established in the literature. For instance, Isaksen et al. (2015a, 2015b) have documented that hot, humid days increase the risk of hospitalization and death in the state of Washington. Choudhary and Vaidyanathan (2014) provide evidence that increases in summer temperatures are associated with an increase in heat stress illness hospitalizations.[8] Focusing on community hospitals, Merrill, Miller, and Steiner (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. Since the increase in hospitalization costs can lead to an increase in insurance payouts, we therefore hypothesize that an increase in summer temperatures can negatively affect the *insurance* sector.

8. 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°C above the seasonal average temperature.

Third, several cognitive biases may be at work to explain the negative impact of rising summer temperatures on several sectors of the economy. High summer temperatures may affect household demand in the *retail sector*. For instance, high temperatures may adversely impact what Starr-McCluer (2000) calls "households' shopping productivity" and in addition may negatively affect customers' perception of wait time (Baker and Cameron 1996) and social interactions with strangers (Griffit and Veitch 1971), inducing them to spend less time shopping. High summer temperatures may also affect the *real estate sector*, as 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). There may also be spillovers between different sectors. For example, if agricultural income falls, agricultural workers may reduce their demand for other goods, affecting sectors such as retail or real estate.

To investigate these conjectured industry-level effects, we break down the total GSP of each state into 12 large industry groups according to the BEA classifications. These groups are listed in descending order of national GDP share in the first column of Table 4 (for a detailed list of industries in each group, see Table A2). The last column of Table 4 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 SIC system to the NAICS, which took place in 1997. In several instances, this substantially affects the composition of specific industries (see, for example, the breakdowns of the "Services" and "Communication/Information" categories in Table A2). Furthermore, the BEA website warns that "users of GDP by state are strongly cautioned against appending the two data series in an attempt to construct a single time series."[9] 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). The split at 1997 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 are strongest in our analysis.[10]

Specifically, for each group of industries j, we estimate the following equation:

$$\Delta y_{i,t}^{j} = \beta_{\text{summer}}^{j} T_{i,\text{summer},t} + \rho \Delta y_{i,t-1}^{j} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{10}$$

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

As a benchmark, we also regress equation (10) where j is total GSP (i.e., we repeat regression (4) for the pre- and post-1997 samples separately and dropping all

9. The full cautionary note is available at https://www.bea.gov/regional/docs/product/.

10. In Figure A2, we document that adding additional seasons to the specification does not alter our main conclusion and only marginally affects the statistical significance of the results. Furthermore, we show that by extending the sample to include the entire pre-1997 sample, it appears that the results are primarily driven by "Agriculture," that is, the sector that has traditionally been the most exposed to high temperature. However, as noted, these results need to be interpreted with caution due to the BEA's recommendation against combining pre- and post-1997 series.

TABLE 4

Industry Analysis

	Pre-1997	Post-1997	Avg. GDP share (%)
Gross state product	−0.188	−0.250	100
	(0.095)**	(0.197)	
	(0.062)***	(0.067)***	
	(0.076)**	(0.156)	
Services†	0.019	−0.206	25.7
	(0.070)	(0.075)***	
	(0.050)	(0.076)***	
	(0.062)	(0.064)***	
Finance, insurance, real estate	−0.209	−0.437	20.5
	(0.241)	(0.384)	
	(0.228)	(0.158)***	
	(0.271)	(0.329)	
Manufacturing	−0.058	0.067	12.9
	(0.215)	(0.623)	
	(0.102)	(0.420)	
	(0.160)	(0.513)	
Government	−0.068	−0.051	12.2
	(0.071)	(0.164)	
	(0.063)	(0.086)	
	(0.070)	(0.128)	
Retail	−0.052	−0.241	6.6
	(0.073)	(0.189)	
	(0.060)	(0.083)***	
	(0.070)	(0.146)*	
Wholesale	−0.158	−0.284	5.9
	(0.104)	(0.171)*	
	(0.062)**	(0.163)*	
	(0.084)*	(0.164)*	
Communication/Information†	−0.235	−0.294	4.5
	(0.088)***	(0.732)	
	(0.092)**	(0.405)	
	(0.068)***	(0.662)	
Construction	−0.224	−0.379	4.4
	(0.236)	(0.446)	
	(0.199)	(0.194)*	
	(0.232)	(0.372)	
Transportation	0.150	0.189	3.0
	(0.125)	(0.221)	
	(0.196)	(0.138)	
	(0.187)	(0.187)	
Utilities	0.338	0.621	1.8
	(0.248)	(0.377)*	
	(0.202)*	(0.230)***	
	(0.220)	(0.264)**	
Mining	−0.152	0.954	1.4
	(0.539)	(1.524)	
	(0.572)	(0.300)***	
	(0.515)	(1.251)	
Agriculture, forestry, fishing	−2.489	−2.203	1.1
	(0.995)**	(0.969)**	
	(0.443)***	(0.502)***	
	(0.952)***	(0.751)***	

(Continued)

TABLE 4

CONTINUED

Industry group analysis: Services and finance, insurance, real estate	Post-1997	Ave GDP share (%)
Professional and business services	−0.219	11.6
	(0.127)*	
	(0.098)**	
	(0.076)***	
Educational services, health care, social assistance	−0.004	7.7
	(0.047)	
	(0.064)	
	(0.043)	
Other services, except government	−0.253	2.6
	(0.136)*	
	(0.103)**	
	(0.099)**	
Food services and drinking places	−0.387	2.0
	(0.155)**	
	(0.148)***	
	(0.127)***	
Arts, entertainment, and recreation	0.417	1.0
	(0.274)	
	(0.203)**	
	(0.229)*	
Accommodation	0.025	0.9
	(0.270)	
	(0.359)	
	(0.335)	
Finance, insurance, real estate		
Real estate	−0.435	11.4
	(0.399)	
	(0.125)***	
	(0.333)	
Federal Reserve banks, credit intermediation, and related services	−0.254	3.6
	(0.463)	
	(0.354)	
	(0.407)	
Insurance, carriers and related activities	−1.299	2.6
	(0.630)**	
	(0.548)**	
	(0.632)**	
Securities, commodity contracts, and investments	−0.287	1.3
	(0.531)	
	(0.337)	
	(0.375)	
Rental and leasing services, lessors of intangible assets	−0.030	1.3
	(0.244)	
	(0.290)	
	(0.169)	
Funds, trusts, and other financial vehicles	1.027	0.2
	(1.142)	
	(1.068)	
	(0.970)	

NOTE: This table reports results for panel regressions of industry output growth, using the entire cross section of 50 states and DC. Industries are classified according to the BEA (see Table A2). All specifications include the lagged dependent variable, and state and year fixed effects; the independent variable is the average summer temperature. 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 pre-1997 sample is 1963–1997 and the post-1997 sample is 1997–2011. The last column reports the share of national GDP that each industry accounts for. Standard errors, clustered by year, by state, and by both dimensions, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

seasonal temperature variables except for the summer). We report the results in the first row of Table 4. Consistent with our previous finding, the table shows that the estimated effect of the average summer temperature on GSP growth appears to be larger in the most recent portion of the sample.

Our results for the estimate of $\beta^{j}_{\text{summer}}$ for each industry group are reported in Table 4. 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 three standard errors, the first clustered by year, the second clustered by state, and the third clustered in both dimensions.

The two largest sectors of the U.S. economy, "Services" and "Finance, insurance, and real estate," account together for almost a half of national GDP and thus warrant further decomposition. Table 4 decomposes these two sectors into an exhaustive list of subcomponents, using the post-1997 sample and the post-1997 NAICS classifications. (We have to omit the pre-1997 sample as the pre-1997 SIC classifications do not offer a decomposition of these two sectors.)

Several important findings emerge from Table 4, especially in the post-1997 sample. Table 4 provides evidence for the conjecture that an increase in the average summer temperature negatively affects the retail and wholesale sectors, which account for 6.6% and 5.9% of national GDP, respectively. In the post-1997 sample, a 1°F increase in the average summer temperature is associated with a 0.24–0.28 percentage points reduction in the output growth of these sectors. Table 4 also provides some evidence for the conjectured effect of summer temperatures on the construction sector, which accounts for 4.4% of national GDP, however, with lesser statistical significance, possibly because of the short sample.

Table 4 also provides evidence for the conjecture that an increase in the average summer temperature negatively affects the real estate sector, which accounts for 11.4% of national GDP. In the post-1997 sample, an increase of 1°F in the average summer temperature is associated with a 0.44 percentage points reduction in the output growth of this sector. While this estimated impact may seem excessively large at first glance, we note that the average volatility of the growth rate of output of the real estate sector is 3.5%, and the average volatility of summer temperature is equal to 1.5. By rescaling the estimated coefficient by the ratio of these volatilities, we obtain a value of -0.19, which can be interpreted as the number of standard deviations that the growth rate of output of this industry moves in response to a one standard deviation movement in summer temperature.[11]

Furthermore, as we previously hypothesized, Table 4 shows that an increase in the average summer temperature negatively affects insurance, insurance carriers, and related activities, which account for 2.6% of national GDP. The effect is substantial: in

11. In Figure A1, we present all of the regression coefficients for the analysis of Table 4 using variables standardized by their volatilities and show that the standardized effect is very similar in the cross section of industries.

the post-1997 sample, a 1°F increase in the average summer temperature is associated with a 1.30 percentage points reduction in the output growth of this sector.[12]

Table 4 shows that an increase in the average summer temperature has a substantial negative effect on agriculture, forestry, and fishing. While the effect on this sector is intuitive and well studied in the literature (see, *inter alia*, Mendelsohn and Neumann 1999, Schlenker and Roberts 2006, 2009, Burke and Emerick 2016), we note that this sector only accounts for about 1% of national GDP. However, its effects also propagate to other sectors. For example, rising summer temperatures are associated with a decline in "Food services and drinking places," which account for about 2% of national GDP (see Table 4). An effect on households' shopping productivity, similar to the one mentioned above for the retail sector, may lead to a decline in the demand for food services and drinking places due to hot summer temperatures.

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 4). This could be due to the higher consumption of energy during warmer summers, which translates into larger revenues for these industries.

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.

3.3 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 Table A3). We then estimate the

12. The growth rate of output in the insurance sector is very large (about 10% per year). We show in Figure A1 that after taking into account this volatility, the effect of temperature in this sector is comparable to effect on real estate.

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)
	(0.216)	(0.233)	(0.235)	(0.186)
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)***
	(0.142)	(0.130)	(0.129)**	(0.157)***
Midwest	0.010	−0.158	0.043	−0.116
	(0.089)	(0.144)	(0.162)	(0.128)
	(0.055)	(0.104)	(0.075)	(0.068)*
	(0.074)	(0.125)	(0.130)	(0.112)
West	−0.000	−0.155	0.028	−0.006
	(0.096)	(0.143)	(0.154)	(0.167)
	(0.060)	(0.077)**	(0.145)	(0.162)
	(0.056)	(0.097)	(0.153)	(0.174)

Note: 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 January–March, spring as April–June, summer is July–September, fall is October–December. Temperatures are in degrees Fahrenheit. The sample is 1957–2012. Standard errors, clustered by year, by state, and by both dimensions, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

regression coefficients of equation (4) for the 10 states with the highest summer temperatures, and successively reestimate these coefficients, each time adding the next temperature-sorted state. The results of this exercise are reported in Figure 4.

The bottom left panel of Figure 4 documents that the estimated summer coefficient for the 10 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 4 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.[13]

We conclude this section by establishing a potential connection with the industry analysis of Section 3.2. As shown in the right panel of Figure 5, the relative contribution of the South to the overall GSP/GDP of the U.S. has substantially increased during our time period (1957–2012). Furthermore, it seems to be the case that this increase in the South's share of GDP has been a widespread phenomenon, involving

13. Our analysis does not preclude the possibility that the average temperature of other seasons may have additional economic effects. For example, an increase in the average winter temperature may plausibly have a positive economic effect in the North, and our empirical evidence cannot reject this null hypothesis. However, we believe that more evidence is needed to fully establish this channel and leave this as an open task for future research.

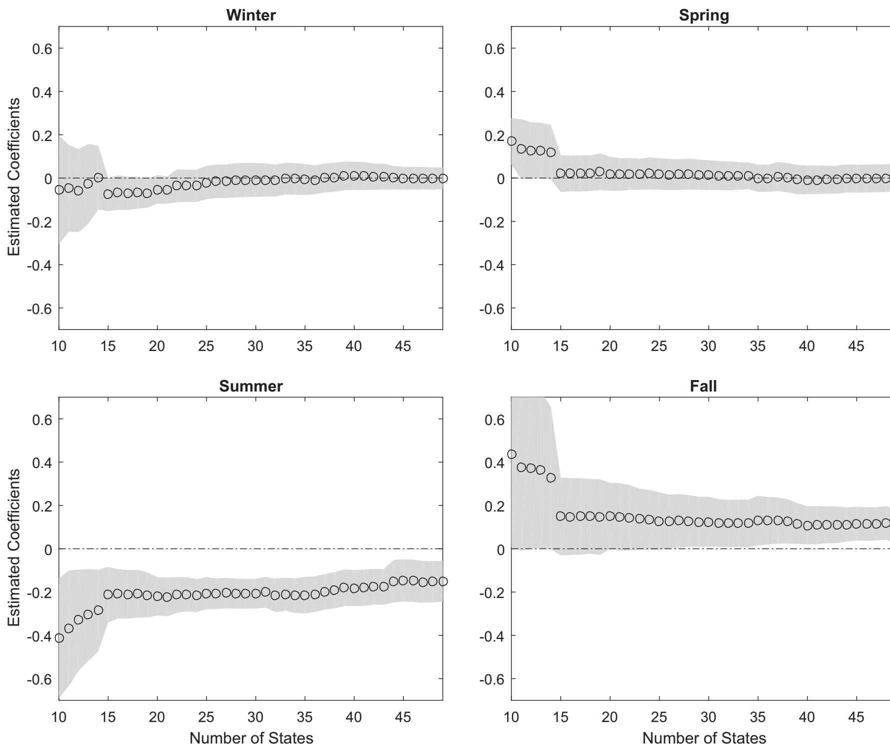

Fig. 4. Effects of Seasonal Temperatures in Temperature-Sorted States.

Note: Each panel reports the estimated coefficients of the average temperature for the corresponding season. Dots correspond to the coefficients estimated for the number of states reported in the horizontal axis. The gray 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.

the entire cross section of industries (see the left panel of Figure 5). Interestingly, the agricultural sector has displayed the smallest percentage increase across the two subsamples. Combined with our regional results in Table 5, this seems to suggest that the increased effect that we estimate in the post-1997 sample is driven by a larger overall contribution of the South to the country's economic activity.

4. ADDITIONAL RESULTS

In this section, we conduct a series of additional exercises to confirm and extend the analysis above. In Section 4.1, we demonstrate that the effect of temperature on GDP growth is not driven by less developed states. Although this result differs from those reported in the literature, even U.S. states that are considered less developed are still

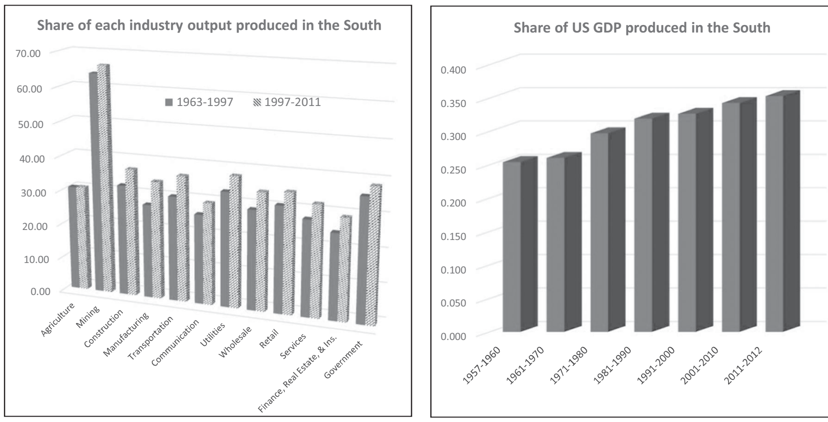

FIG. 5. Percent of Total U.S. GDP Produced in the South Region.

NOTE: The left panel reports the breakdown by industry. The right panel reports the share of total GDP produced in the South by decade (or fraction of it) from 1957 to 2012.

highly developed according to common measures of global poverty. In Section 4.2, we combine the estimated impact coefficients from Section 2 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 4.3, we conclude our investigation by showing that our main finding on the effect of summer temperatures is robust to alternative specifications.

4.1 Development and Temperature

In this section, we explore the interaction between the level of development of a state and seasonal temperatures. Specifically, we define development levels according to the Human Development Index (HDI) for American states developed by Lewis and Burd-Sharps (2014). We introduce an HDI indicator variable equal to 1 for states with values of the HDI less than or equal to 4.5, which corresponds to the bottom 20% of the distribution. With the exception of Idaho (which is located in the West region), all of the less developed states are in the South region. Specifically, the following states in the South are classified as states with “low development”: Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, South Carolina, Tennessee, and West Virginia. The following states in the South are instead classified as states with “high development”: Delaware, D.C., Florida, Georgia, Maryland, North Carolina, Texas, and Virginia.

We use the following regression specification to investigate the hypothesis that less developed states are driving the strong negative effect of summer temperature on GSP growth in the South:

$$\Delta y_{i,t} = \sum_{s \in \mathcal{S}} \left(\beta_s T_{i,s,t} + \delta_s T_{i,s,t} \cdot I[HDI_i] \right) + \rho \cdot \Delta y_{i,t-1} + \alpha_i + \alpha_t + \varepsilon_{i,t}, \quad (11)$$

TABLE 6

Effects of Seasonal Temperature by Development Level

	Winter	Spring	Summer	Fall
Panel A: South				
β_s	−0.111	0.139	−0.375	0.585
	(0.188)	(0.185)	(0.179)**	(0.203)***
	(0.069)	(0.116)	(0.090)***	(0.065)***
δ_s	0.053	0.068	0.131	−0.042
	(0.072)	(0.136)	(0.120)	(0.124)
	(0.046)	(0.111)	(0.064) **	(0.060)
Panel B: U.S.				
β_s	0.005	−0.008	−0.155	0.099
	(0.049)	(0.065)	(0.075)**	(0.052)*
	(0.026)	(0.032)	(0.050)***	(0.040)**
δ_s	−0.031	0.121	0.003	0.036
	(0.055)	(0.106)	(0.113)	(0.111)
	(0.043)	(0.075)	(0.063)	(0.059)

Note: Results of estimating equation (11). HDI is an indicator equal to 1 for states with HDI value less than or equal to 4.5. The sample is 1957–2012. Standard errors are in parentheses. The first set of standard errors is clustered by year and the second set of standard errors is clustered by state. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

where $\Delta y_{i,t}$ denotes GSP growth in state i in year t, and $T_{i,s,t}$ denotes the temperature in degrees Fahrenheit in state i, year t, and season s. We include the interaction between $I[HDI_i]$, an indicator for low development, and seasonal temperatures. We also include the lagged GSP growth rate as a control to capture the degree of autocorrelation of the dependent variable, in addition to α_i and α_t, which denote state and year fixed effects.

Panel A of Table 6 reports the results of estimating the specification above in the South region and Panel B reports the results for the whole U.S. Two sets of standard errors are reported in the table, the first clustered by year and the second clustered by state.[14] Both in the South region and in the whole country, the coefficient on summer temperature is negative and significant and the coefficient on the interaction of the indicator for lower HDI and summer temperature is positive and marginally significant. This indicates that the negative effect of summer temperature documented in Table 5 is not driven by less developed states.[15]

The results reported in Table 6 are likely driven by the different industrial composition of more and less developed states in the South, with GSP in states with higher development more highly concentrated in industries exposed to summer

14. We report only the standard errors clustered in one dimension, because the standard errors clustered in two dimensions become unreliable when the cluster size shrinks.

15. We have replicated the analysis in equation (11) by focusing on the 10 hottest states in the United States. The results of our estimation for this subset of states indicate that the coefficient β_{summer} is equal to -0.485 with standard errors of 0.239 and 0.153 (depending on clustering), while the coefficient δ_{summer} is equal to 0.180 with standard errors of 0.154 and 0.110 (depending on clustering). This supports the idea that the negative effect of temperature on GDP growth is primarily driven by the higher development states.

temperature. For example, in the South, the finance sector constitutes a greater percent of GSP in high development states (22% for 1997–2011) than in less developed states (14% for 1997–2011). Although less developed states have a greater percent of GSP from the agricultural sector, agriculture accounts for a very small fraction of total GSP (see Figure 5).

These results likely differ from those reported in the literature because even U.S. states that are considered less developed are still well above the poverty line, according to the most common measures of poverty. For example, Arkansas, which is ranked second from the bottom in terms of the American HDI, has a 2016 GDP per capita of about $36,000. According to the IMF, this is comparable to the GDP per capita of developed countries such as Israel, Italy, and Spain. Although it is certainly true that there is a marked socioeconomic North–South divide in the United States, Southern states are still highly developed according to most international metrics. This implies that the channel through which temperature affects GDP in this part of the country must be distinct from that typically established for developing economies. We believe that our evidence on the widespread effect of temperature on sectors other than agriculture is the key to explaining this result.

4.2 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 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 2 remain unchanged over the long horizon.

To quantify the potential long-term relevance of the coefficients estimated in Section 2, we employ temperature projections obtained from the Climate Wizard tool (http://ClimateWizard.org) developed by Girvetz et al. (2009). We use this tool to obtain projected monthly average temperatures for the U.S. for the period 2070–2099 from 16 general circulation models (GCMs) under three different IPCC greenhouse gas emissions scenarios: A2 (high emissions), A1B (medium emissions), and B1 (low emissions). For each model and scenario, we consider both the minimum and maximum projected temperature change in our analysis.

We combine each set of temperature projections with the impact coefficients that we estimated in Section 2. 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 compute the projected impact on the growth rate of GDP as:

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

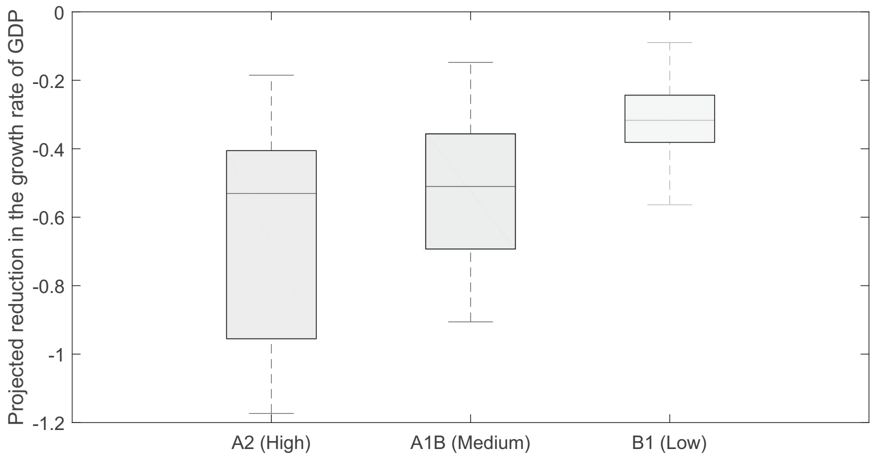

FIG. 6. Projected Reduction in the Growth Rate of GDP for the Period 2070–2099 under Three Emission Scenarios.

NOTE: For each scenario, the bottom and top lines denote the minimum and maximum projected impact, the bottom and top of the rectangle are the first and third quartiles of the distribution of projected impacts, while the horizontal line within the rectangle is the median projected impact.

where $E[\Delta T_s]$ and $\hat{\beta}_s$ denote the expected change in the average temperature of season s and the impact coefficient of season s, respectively. Throughout our analysis, we use $\hat{\beta}_{\text{summer}} = -0.154$ and $\hat{\beta}_{\text{fall}} = 0.102$, as reported in Table 1.

We report the results of our analysis in Figure 6. Under the most conservative emission scenario (B1), the projected trend in rising temperatures is expected to reduce the growth rate of U.S. output by 0.2–0.4 percentage points over the next 100 years, depending on the specific GCM 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 reduction of the growth rate by up to 10%.

The results are more dramatic when we use the projections obtained under the more aggressive emission scenarios. For instance, under the high emission scenario (A2), the estimated reductions in output growth due to rising temperatures could be as large as 1.2 percentage point. 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 roughly a third of the historical average nominal U.S. GDP growth rate.

4.3 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 7. Throughout the table (except the row "Spatial correlation"), we report three standard errors, one clustered by year, one clustered by state, and one in both dimensions, with the corresponding

TABLE 7

Robustness Checks

	Winter	Spring	Summer	Fall
Alternative panel weights				
Time-varying GSP	0.008	−0.008	−0.148	0.105
	(0.051)	(0.067)	(0.076)*	(0.058)*
	(0.026)	(0.030)	(0.043)***	(0.042)**
	(0.047)	(0.051)	(0.066)**	(0.057)*
State population	0.028	−0.024	−0.132	0.131
	(0.053)	(0.069)	(0.071)*	(0.061)**
	(0.025)	(0.039)	(0.039)***	(0.043)***
	(0.048)	(0.060)	(0.060)**	(0.062)**
State area	0.018	0.012	−0.098	0.079
	(0.062)	(0.074)	(0.066)	(0.063)
	(0.033)	(0.045)	(0.054)*	(0.063)
	(0.058)	(0.068)	(0.059)*	(0.075)
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)	(0.048)**	(0.040)**
	(0.043)	(0.055)	(0.064)*	(0.053)*
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)
	(0.042)*	(0.054)	(0.109)*	(0.061)
Private industries only	0.013	0.010	−0.207	0.114
	(0.063)	(0.083)	(0.087)**	(0.069)*
	(0.029)	(0.041)	(0.060)***	(0.049)**
	(0.055)	(0.065)	(0.076)***	(0.067)*
Alternative definitions of seasons				
Meteorological	0.025	−0.040	−0.083	0.025
	(0.043)	(0.053)	(0.074)	(0.055)
	(0.016)	(0.038)	(0.038)**	(0.033)
	(0.033)	(0.044)	(0.059)	(0.049)
Core seasonal months	0.015	−0.026	−0.145	0.036
	(0.041)	(0.050)	(0.066)**	(0.050)
	(0.016)	(0.023)	(0.033)***	(0.027)
	(0.035)	(0.035)	(0.055)***	(0.045)
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)	(0.028)	(0.041)***	(0.034)***
	(0.043)	(0.052)	(0.061)**	(0.051)*
Pre-1950 deseasonalization	0.001	0.003	−0.154	0.102
	(0.049)	(0.065)	(0.072)**	(0.055)*
	(0.025)	(0.032)	(0.047)***	(0.040)***
	(0.044)	(0.051)	(0.065)**	(0.054)*

(Continued)

TABLE 7

CONTINUED

	Winter	Spring	Summer	Fall
Alternative temperature data				
Nondeseasonalized 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)***
	(0.038)	(0.044)	(0.058)***	(0.044)**
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)**
	(0.043)	(0.057)	(0.069)**	(0.052)*
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)***
	(0.045)	(0.046)	(0.061)**	(0.052)**
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)**
	(0.049)	(0.058)	(0.073)**	(0.053)
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)***
	(0.044)	(0.051)	(0.064)**	(0.054)**

NOTE: 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 January–February, spring is April–May, summer is July–August, and fall is November–December. In the row "Spatial correlation," all states are equally weighted. Standard errors, clustered by year, by state, and by both dimensions, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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 section "GSP weights" of the Appendix). The results indicate that the signs of the estimated coefficients are generally aligned with the main findings in Section 2.

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 7). Specifically, in the row labeled “Meteorological,” all seasons are shifted backward by 1 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 7, 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”). Section “Deseasonalization” in the Appendix describes the method that we used to deseasonalize the temperature data. Furthermore, in the row “Nondeseasonalized gridded temp.,” we employ gridded temperature data that are not deseasonalized from the NOAA nClimDiv data set to show that the deseasonalization of weather data does not drive our results.

In the panel labeled “Other” in Table 7, 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.

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 section "Deseasonalization" in the Appendix 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 7 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 of 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 noncontiguous 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.[16]

5. 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.

16. In Appendix A.6, we provide a series of further robustness checks.

Our results are informative for the calibration of the climate damage functions in general equilibrium models, and they also should be helpful in advancing the analysis of the long-term effects of climate change (e.g., Stern 2007, Bansal and Ochoa 2011, Nordhaus and Sztorc 2013, Giglio et al. 2015, Donadelli et al. 2017). These results highlight the importance of improving the next generation of equilibrium models for the environment along two dimensions. First, these models should account for the heterogeneous effects that rising temperatures have on the cross section of industries. Second, these models should explicitly model 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). Future research should employ methodologies from these studies to further investigate potential nonlinearities in the effects of seasonal temperatures.

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

TABLE A1

Correlation of Individual Stations in an 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	

Note: 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).

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

Note: Definitions from the Bureau of Economic Analysis.

a currently active weather station in that area. The data series is then extended further by using another weather station in the area.[17] For example, the weather data series for the Nashville, TN, area is compiled from three individual weather stations over the time period 1871–2014.[18]

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 eight meet the inclusion criteria, and there are 83 stations in the Las Vegas area and seven meet the inclusion criteria. The correlations in daily temperature reported across stations are greater than 0.99.

17. http://threadex.rcc-acis.org/
18. http://threadex.rcc-acis.org/threadex/process_records

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			

NOTE: 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 A4

P-VALUES FOR WALD TESTS OF GROWTH VERSUS LEVEL EFFECTS

	Winter	Spring	Summer	Fall
Two lags	[0.547]	[0.148]	[0.004]	[0.101]
	[0.148]	[0.013]	[0.000]	[0.008]
Five lags	[0.373]	[0.043]	[0.008]	[0.410]
	[0.039]	[0.011]	[0.002]	[0.124]
One lag, no LDV	[0.835]	[0.189]	[0.004]	[0.022]
	[0.663]	[0.030]	[0.000]	[0.004]

NOTE: This table reports results of robustness checks of growth versus level regression (8). Each row reports the p-values, the first clustered by year and the second clustered by state, for the Wald test of whether $\beta + \sum \beta_{\text{lag}}$ is significantly different from zero. The first two rows includes two and five lags of temperatures, respectively. The last row includes one lag of temperature and excludes the lagged dependent variable (GSP growth). Temperatures are in degrees Fahrenheit. The sample is 1957–2012. The regressions are weighted by constant GSP shares.

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 and the 20-year period beginning in 1969 has the

TABLE A5

AUTOCORRELATION OF STATES' GDP GROWTH RATES

State	AC(1)	(S.E.)	State	AC(1)	(S.E.)
Alabama	0.492***	(0.120)	Montana	0.286**	(0.130)
Alaska	0.270**	(0.133)	Nebraska	−0.019	(0.135)
Arizona	0.623***	(0.108)	Nevada	0.673***	(0.099)
Arkansas	0.444***	(0.125)	New Hampshire	0.420***	(0.124)
California	0.658***	(0.101)	New Jersey	0.632***	(0.104)
Colorado	0.668***	(0.102)	New Mexico	0.523***	(0.117)
Connecticut	0.612***	(0.109)	New York	0.498***	(0.117)
Delaware	0.181	(0.133)	North Carolina	0.398***	(0.124)
District of Columbia	0.413***	(0.127)	North Dakota	0.017	(0.139)
Florida	0.755***	(0.087)	Ohio	0.319**	(0.130)
Georgia	0.614***	(0.106)	Oklahoma	0.543***	(0.116)
Hawaii	0.663***	(0.100)	Oregon	0.208	(0.131)
Idaho	0.415***	(0.125)	Pennsylvania	0.425***	(0.121)
Illinois	0.367***	(0.126)	Rhode Island	0.523***	(0.114)
Indiana	0.139	(0.134)	South Carolina	0.520***	(0.113)
Iowa	0.141	(0.136)	South Dakota	−0.128	(0.136)
Kansas	0.405***	(0.123)	Tennessee	0.413***	(0.121)
Kentucky	0.334***	(0.129)	Texas	0.542***	(0.114)
Louisiana	0.474***	(0.122)	Utah	0.640***	(0.106)
Maine	0.439***	(0.122)	Vermont	0.212	(0.133)
Maryland	0.604***	(0.105)	Virginia	0.621***	(0.105)
Massachusetts	0.671***	(0.099)	Washington	0.518***	(0.115)
Michigan	0.197	(0.135)	West Virginia	0.425***	(0.125)
Minnesota	0.312**	(0.128)	Wisconsin	0.454***	(0.120)
Mississippi	0.399***	(0.123)	Wyoming	0.462***	(0.123)
Missouri	0.345***	(0.127)			

NOTE: This table reports the first-order autocorrelations of nominal GDP growth rates for each U.S. state. The numbers in parenthesis denote standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

TABLE A6

CORRELATIONS OF SEASONAL TEMPERATURES

	Winter/Spring	Winter/Summmer	Winter/Fall	Spring/Summer	Spring/Fall	Summer/Fall
Median	0.208	0.144	0.044	0.293	0.185	0.133
90% CI	[−0.103, 0.432]	[−0.114, 0.327]	[−0.189, 0.166]	[0.093, 0.448]	[−0.048, 0.325]	[−0.018, 0.376]

NOTE: This table reports the median seasonal temperature correlations along with the 90% confidence intervals for the cross section of U.S. states.

TABLE A7

ROBUSTNESS OF TABLE 1 (USING GRIDDED DATA)

	Winter	Spring	Summer	Fall
Panel analysis	0.001	−0.005	−0.167	0.100
	(0.042)	(0.057)	(0.064)***	(0.047)**
	(0.023)	(0.028)	(0.047)***	(0.035)***

NOTE: See notes to Table 1 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A8

Robustness of Table 2 (Using Gridded Data)

	Winter	Spring	Summer	Fall
Contemporaneous temp.	−0.004	−0.015	−0.181	0.104
	(0.044)	(0.052)	(0.066)***	(0.044)**
	(0.024)	(0.028)	(0.048)***	(0.035)***
One-year lagged temp.	0.006	0.094	−0.151	0.042
	(0.046)	(0.051)*	(0.069)**	(0.051)
	(0.022)	(0.032)***	(0.050)***	(0.025)*
Sum of coefficients	0.002	0.079	−0.332	0.146
	(0.074)	(0.075)	(0.096)***	(0.065)**
	(0.029)	(0.041)*	(0.080)***	(0.049)***
Wald test's p-value	(0.978)	(0.297)	(0.001)	(0.030)
	(0.944)	(0.058)	(0.000)	(0.004)

Note: See notes to Table 2 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A9

Robustness of Table 3 (Using Gridded Data)

	Winter	Spring	Summer	Fall
Productivity	−0.033	−0.037	−0.145	0.120
	(0.055)	(0.062)	(0.086)*	(0.051)**
	(0.034)	(0.028)	(0.049)***	(0.046)***
Employment	0.014	−0.073	0.022	−0.008
	(0.027)	(0.042)*	(0.057)	(0.036)
	(0.013)	(0.042)*	(0.032)	(0.015)

Note: See notes to Table 3 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A10

Robustness of Table 4 (Using Gridded Data)

	Pre-1997	Post-1997	Avg. GDP share (%)
Gross state product	−0.212	−0.222	100
	(0.091)**	(0.183)	
	(0.064)***	(0.060)***	
Services	0.020	−0.184	25.7
	(0.058)	(0.066)***	
	(0.054)	(0.076)**	
Finance, insurance, real estate	−0.255	−0.356	20.5
	(0.233)	(0.340)	
	(0.233)	(0.140)**	
Manufacturing	−0.082	0.042	12.9
	(0.194)	(0.624)	
	(0.083)	(0.377)	

(Continued)

TABLE A10
CONTINUED

	Pre-1997	Post-1997	Avg. GDP share (%)
Government	−0.045 (0.065) (0.051)	−0.036 (0.142) (0.085)	12.2
Retail	−0.084 (0.060) (0.063)	−0.285 (0.174) (0.093)***	6.6
Wholesale	−0.176 (0.103)* (0.060)***	−0.267 (0.171) (0.151)*	5.9
Communication/Information	−0.224 (0.091)** (0.109)**	−0.262 (0.681) (0.406)	4.5
Construction	−0.186 (0.205) (0.208)	−0.415 (0.400) (0.154)***	4.4
Transportation	0.091 (0.109) (0.167)	0.188 (0.225) (0.159)	3.0
Utilities	0.205 (0.187) (0.197)	0.645 (0.386)* (0.223)***	1.8
Mining	−0.521 (0.508) (0.413)	0.662 (1.295) (0.303)**	1.4
Agriculture, forestry, fishing	−2.634 (0.940)*** (0.445)***	−2.022 (0.892)** (0.468)***	1.1

NOTE: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

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 A11

Robustness of Table 4 (Using Gridded Data)

	Post-1997	Ave GDP share (%)
Services		
Professional and business services	−0.192	11.6
	(0.122)	
	(0.103)*	
Educational services, health care, social assistance	0.024	7.7
	(0.050)	
	(0.060)	
Other services, except government	−0.217	2.6
	(0.132)*	
	(0.106)**	
Food services and drinking places	−0.415	2.0
	(0.144)***	
	(0.127)***	
Arts, entertainment, and recreation	0.375	1.0
	(0.242)	
	(0.202)*	
Accommodation	0.013	0.9
	(0.215)	
	(0.326)	
Finance, insurance, real estate		
Real estate	−0.441	11.4
	(0.358)	
	(0.112)***	
Federal Reserve banks, credit intermediation, and related services	−0.160	3.6
	(0.400)	
	(0.311)	
Insurance, carriers, and related activities	−0.995	2.6
	(0.590)*	
	(0.458)**	
Securities, commodity contracts, and investments	−0.218	1.3
	(0.508)	
	(0.296)	
Rental and leasing services, lessors of intangible assets	−0.012	1.3
	(0.227)	
	(0.277)	
Funds, trusts, and other financial vehicles	0.702	0.2
	(1.171)	
	(1.041)	

Note: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A12

ROBUSTNESS OF TABLE 5 (USING GRIDDED DATA)

	Winter	Spring	Summer	Fall
North	0.195	0.077	0.089	0.084
	(0.130)	(0.196)	(0.191)	(0.170)
	(0.120)	(0.159)	(0.114)	(0.167)
South	−0.108	0.162	−0.281	0.570
	(0.163)	(0.157)	(0.152)*	(0.184)***
	(0.084)	(0.064)**	(0.114)**	(0.077)***
Midwest	0.006	−0.117	−0.032	−0.100
	(0.068)	(0.108)	(0.116)	(0.104)
	(0.041)	(0.085)	(0.073)	(0.060)*
West	0.042	−0.145	−0.007	0.050
	(0.088)	(0.118)	(0.156)	(0.152)
	(0.067)	(0.060)**	(0.195)	(0.191)

NOTE: See notes to Table 5 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A13

ROBUSTNESS OF TABLE 1 (USING TEMPERATURE DATA AGGREGATED BY POPULATION)

	Whole Year	Winter	Spring	Summer	Fall
Panel analysis	0.017	0.012	−0.004	−0.129	0.094
	(0.109)	(0.048)	(0.066)	(0.074)*	(0.057)*
	(0.057)	(0.023)	(0.028)	(0.041)***	(0.034)***

NOTE: See notes to Table 1 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

A.2 Additional Details of the Empirical Analysis

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

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

In the row labeled "Pre-1950 deseasonalization" in Table 7, we estimate γ_m and α_j using weather data up to only 1950.

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

TABLE A14

Robustness of Table 2 (Using Temperature Data Aggregated by Population)

	Winter	Spring	Summer	Fall
Contemporaneous temp.	0.009	−0.023	−0.142	0.100
	(0.051)	(0.062)	(0.077)*	(0.052)*
	(0.025)	(0.030)	(0.040)***	(0.033)***
One-year lagged temp.	0.011	0.132	−0.145	0.044
	(0.049)	(0.061)**	(0.078)*	(0.062)
	(0.026)	(0.040)***	(0.056)***	(0.028)
Sum of coefficients	0.020	0.110	-0.287	0.144
	(0.079)	(0.087)	(0.110)***	(0.082)*
	(0.029)	(0.042)***	(0.075)***	(0.044)***
Wald test's p-value	[0.804]	[0.211]	[0.011]	[0.085]
	[0.507]	[0.012]	[0.000]	[0.002]

Note: See notes to Table 2 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A15

Robustness of Table 3 (Using Temperature Data Aggregated by Population)

	Winter	Spring	Summer	Fall
Productivity	−0.029	−0.045	−0.113	0.148
	(0.069)	(0.073)	(0.091)	(0.051)***
	(0.040)	(0.034)	(0.048)**	(0.053)***
Employment	0.015	−0.082	0.008	−0.023
	(0.032)	(0.050)*	(0.058)	(0.041)
	(0.015)	(0.047)*	(0.035)	(0.016)

Note: See notes to Table 3 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

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 2) 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 7, 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 3.2, with industry output data and classifications from the Bureau of Economic Analysis. The column "Pre-1997 classification" uses the industry group

TABLE A16

Robustness of Table 4 (Using Temperature Data Aggregated by Population)

	Pre-1997	Post-1997	Avg. GDP share (%)
Gross state product	−0.164 (0.104) (0.054)***	−0.187 (0.205) (0.072)***	100
Services†	0.016 (0.072) (0.049)	−0.122 (0.087) (0.070)*	25.7
Finance, insurance, real estate	−0.249 (0.221) (0.193)	−0.418 (0.373) (0.144)***	20.5
Manufacturing	−0.019 (0.217) (0.098)	0.333 (0.606) (0.451)	12.9
Government	−0.047 (0.077) (0.051)	−0.038 (0.158) (0.081)	12.2
Retail	−0.041 (0.071) (0.056)	−0.181 (0.185) (0.090)**	6.6
Wholesale	−0.090 (0.105) (0.062)	−0.217 (0.175) (0.154)	5.9
Communication/Information†	−0.182 (0.102)* (0.080)**	−0.269 (0.673) (0.355)	4.5
Construction	−0.159 (0.234) (0.185)	−0.390 (0.424) (0.190)**	4.4
Transportation	0.168 (0.131) (0.191)	0.249 (0.195) (0.119)**	3.0
Utilities	0.357 (0.229) (0.174)**	0.600 (0.366)* (0.206)***	1.8
Mining	0.048 (0.543) (0.522)	0.596 (1.400) (0.442)	1.4
Agriculture, forestry, fishing	−2.500 (0.941)*** (0.390)***	−2.118 (0.981)** (0.478)***	1.1

Note: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

categories of the SIC. The column "Post-1997 classification" uses the industry group categories of the NAICS.

A.4 Definition of U.S. Regions and Ranking of States

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

TABLE A17

Robustness of Table 4 (Using Temperature Data Aggregated by Population)

	Post-1997	Ave GDP share (%)
Services		
Professional and business services	−0.083	11.6
	(0.145)	
	(0.085)	
Educational services, health care, social assistance	−0.011	7.7
	(0.045)	
	(0.064)	
Other services, except government	−0.136	2.6
	(0.122)	
	(0.092)	
Food services and drinking places	−0.284	2.0
	(0.146)*	
	(0.162)*	
Arts, entertainment, and recreation	0.354	1.0
	(0.268)	
	(0.168)**	
Accommodation	0.091	0.9
	(0.246)	
	(0.330)	
Finance, insurance, real estate		
Real estate	−0.407	11.4
	(0.387)	
	(0.113)***	
Federal Reserve banks, credit intermediation, and related services	−0.184	3.6
	(0.415)	
	(0.280)	
Insurance, carriers and related activities	−1.419	2.6
	(0.612)**	
	(0.539)***	
Securities, commodity contracts, and investments	−0.207	1.3
	(0.512)	
	(0.297)	
Rental and leasing services, lessors of intangible assets	0.008	1.3
	(0.272)	
	(0.271)	
Funds, trusts, and other financial vehicles	1.243	0.2
	(1.201)	
	(0.897)	

Note: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

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;

TABLE A18

Robustness of Table 5 (Using Temperature Data Aggregated by Population)

	Winter	Spring	Summer	Fall
North	0.345	0.071	0.219	−0.355
	(0.219)	(0.285)	(0.271)	(0.266)
	(0.261)	(0.191)	(0.240)	(0.144)**
South	−0.056	0.058	−0.263	0.515
	(0.153)	(0.144)	(0.161)	(0.194)***
	(0.080)	(0.082)	(0.069)***	(0.089)***
Midwest	0.001	−0.174	0.093	−0.089
	(0.092)	(0.156)	(0.185)	(0.139)
	(0.071)	(0.118)	(0.090)	(0.082)
West	0.052	−0.145	0.102	−0.030
	(0.094)	(0.143)	(0.138)	(0.151)
	(0.050)	(0.067)**	(0.144)	(0.147)

Note: See notes to Table 5 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A19

Robustness of Table 3 (Including 1-Year Lag of Temperature)

	Winter	Spring	Summer	Fall
Productivity contemporaneous temp.	−0.050	−0.040	−0.167	0.163
	(0.066)	(0.064)	(0.090)*	(0.054)***
	(0.035)	(0.040)	(0.055)***	(0.076)**
Productivity 1-year lag	−0.019	−0.023	−0.083	0.062
	(0.067)	(0.065)	(0.119)	(0.071)
	(0.055)	(0.026)	(0.058)	(0.119)
Sum of coefficients	−0.069	−0.063	−0.250	0.225
	(0.114)	(0.099)	(0.141)*	(0.112)**
	(0.067)	(0.046)	(0.068)***	(0.182)
Wald test's p-value	[0.553]	[0.531]	[0.092]	[0.058]
	[0.309]	[0.176]	[0.001]	[0.223]
Employment contemporaneous temp.	0.016	−0.083	0.002	−0.018
	(0.026)	(0.040)**	(0.064)	(0.047)
	(0.016)	(0.050)*	(0.039)	(0.028)
Employment 1-year lag temp.	0.074	0.027	−0.136	−0.007
	(0.035)**	(0.042)	(0.052)***	(0.048)
	(0.019)***	(0.024)	(0.050)***	(0.022)
Sum of coefficients	0.090	−0.056	−0.134	−0.025
	(0.044)**	(0.054)	(0.098)	(0.082)
	(0.031)***	(0.034)	(0.065)**	(0.035)
Wald test's p-value	[0.053]	[0.317]	[0.187]	[0.762]
	[0.005]	[0.108]	[0.045]	[0.474]

Note: See notes to Table 3 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A20

Robustness of Table 4 Column 1 (Including 1-Year Lag of Temperature)

	Contemp. temp.	One-year lag temp.	Sum of coeff.	Wald test's p-value
Gross state product	−0.186	−0.116	−0.301	
	(0.095)*	(0.113)	(0.158)*	[0.065]
	(0.060)***	(0.098)	(0.123)**	[0.018]
Services†	0.022	−0.187	−0.164	
	(0.067)	(0.061)***	(0.092)*	[0.084]
	(0.049)	(0.049)***	(0.079)**	[0.042]
Finance, insurance, real estate	−0.205	−0.207	−0.412	
	(0.243)	(0.177)	(0.331)	[0.222]
	(0.235)	(0.143)	(0.219)*	[0.066]
Manufacturing	−0.052	−0.221	−0.274	
	(0.218)	(0.192)	(0.254)	[0.289]
	(0.104)	(0.171)	(0.153)*	[0.079]
Government	−0.068	0.019	−0.049	
	(0.071)	(0.062)	(0.095)	[0.608]
	(0.063)	(0.070)	(0.107)	[0.647]
Retail	−0.050	−0.075	−0.125	
	(0.075)	(0.081)	(0.102)	[0.227]
	(0.060)	(0.059)	(0.079)	[0.119]
Wholesale	−0.153	−0.161	−0.314	
	(0.104)	(0.107)	(0.166)*	[0.068]
	(0.062)**	(0.087)*	(0.104)***	[0.004]
Communication/Information†	−0.238	0.073	−0.164	
	(0.088)***	(0.101)	(0.148)	[0.275]
	(0.091)***	(0.095)	(0.122)	[0.185]
Construction	−0.216	−0.471	−0.688	
	(0.238)	(0.256)*	(0.383)*	[0.082]
	(0.184)	(0.230)**	(0.360)*	[0.062]
Transportation	0.151	−0.037	0.114	
	(0.124)	(0.149)	(0.213)	[0.595]
	(0.195)	(0.097)	(0.254)	[0.654]
Utilities	0.337	0.028	0.364	
	(0.249)	(0.184)	(0.283)	[0.207]
	(0.202)*	(0.160)	(0.258)	[0.164]
Mining	−0.162	0.138	−0.024	
	(0.538)	(0.706)	(0.817)	[0.977]
	(0.539)	(0.730)	(1.189)	[0.984]
Agriculture, forestry, fishing	−2.556	1.338	−1.218	
	(0.966)***	(0.700)*	(1.292)	[0.353]
	(0.444)***	(0.316)***	(0.369)***	[0.002]

Note: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

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

Table A3 displays each state's 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 4.

TABLE A21

ROBUSTNESS OF TABLE 4, COLUMN 2 (INCLUDING 1-YEAR LAG OF TEMPERATURE)

	Contemp. temp.	One-year lag temp.	Sum of coeff.	Wald test's p-value
Gross state product	−0.269	−0.223	−0.492	
	(0.183)	(0.151)	(0.212)**	[0.039]
	(0.069)***	(0.090)**	(0.121)***	[0.000]
Services†	−0.230	−0.242	−0.472	
	(0.068)***	(0.132)*	(0.162)***	[0.013]
	(0.080)***	(0.127)*	(0.176)***	[0.010]
Finance, insurance, real estate	−0.454	−0.184	−0.638	
	(0.385)	(0.278)	(0.561)	[0.278]
	(0.155)***	(0.128)	(0.205)***	[0.003]
Manufacturing	0.014	−0.576	−0.562	
	(0.622)	(0.515)	(0.821)	[0.507]
	(0.410)	(0.416)	(0.492)	[0.259]
Government	−0.071	−0.267	−0.338	
	(0.159)	(0.148)*	(0.238)	[0.180]
	(0.085)	(0.141)*	(0.163)**	[0.043]
Retail	−0.251	−0.093	−0.343	
	(0.200)	(0.202)	(0.333)	[0.323]
	(0.083)***	(0.070)	(0.103)***	[0.002]
Wholesale	−0.294	−0.116	−0.410	
	(0.173)*	(0.124)	(0.231)*	[0.101]
	(0.160)*	(0.081)	(0.157)***	[0.012]
Communication/Information†	−0.298	−0.045	−0.343	
	(0.739)	(0.291)	(0.870)	[0.701]
	(0.388)	(0.323)	(0.321)	[0.290]
Construction	−0.410	−0.390	−0.800	
	(0.442)	(0.338)	(0.612)	[0.215]
	(0.189)**	(0.186)**	(0.267)***	[0.004]
Transportation	0.201	0.167	0.368	
	(0.216)	(0.256)	(0.367)	[0.337]
	(0.140)	(0.145)	(0.254)	[0.153]
Utilities	0.605	−0.209	0.396	
	(0.341)*	(0.509)	(0.488)	[0.433]
	(0.252)**	(0.387)	(0.580)	[0.498]
Mining	0.844	1.673	2.516	
	(1.593)	(1.361)	(1.848)	[0.198]
	(0.356)**	(0.718)**	(0.645)***	[0.000]
Agriculture, forestry, fishing	−2.091	1.817	−0.274	
	(0.999)**	(1.106)*	(1.764)	[0.879]
	(0.463)***	(0.758)**	(0.852)	[0.749]

NOTE: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

A.5 Additional Results and Robustness Checks

Robustness for growth versus level test. Table A4 provides several robustness checks for the test of growth versus level effects reported in Table 2. The table reports the p-value of the Wald test for the hypothesis that $\beta_s + \sum \beta_{\text{lag},s} = 0$ for each season s, where the sum is over all the lags of seasonal temperature. In the table, we include two

TABLE A22

Robustness of Table 4 (Including 1-Year Lag of Temperature)

	Contemp. temp.	One-year lag temp.	Sum of coeff.	Wald test's p-value
Services				
Professional and business services	−0.258	−0.391	−0.649	
	(0.103)**	(0.223)*	(0.234)***	[0.017]
	(0.113)**	(0.225)*	(0.307)**	[0.039]
Educational services, health care, social assistance	−0.007	−0.022	−0.028	
	(0.048)	(0.061)	(0.085)	[0.746]
	(0.065)	(0.047)	(0.087)	[0.745]
Other services, except government	−0.274	−0.257	−0.531	
	(0.147)*	(0.178)	(0.277)*	[0.079]
	(0.104)***	(0.154)*	(0.214)**	[0.016]
Food services and drinking places	−0.392	−0.063	−0.455	
	(0.158)**	(0.243)	(0.321)	[0.181]
	(0.148)***	(0.067)	(0.180)**	[0.015]
Arts, entertainment, and recreation	0.371	−0.439	−0.068	
	(0.258)	(0.247)*	(0.419)	[0.873]
	(0.202)*	(0.160)***	(0.281)	[0.809]
Accommodation	0.015	−0.182	−0.167	
	(0.275)	(0.240)	(0.460)	[0.723]
	(0.365)	(0.177)	(0.489)	[0.734]
Finance, insurance, real estate				
Real estate	−0.460	−0.268	−0.728	
	(0.402)	(0.234)	(0.572)	[0.227]
	(0.121)***	(0.112)**	(0.181)***	[0.000]
Federal Reserve banks, credit intermediation, and related services	−0.271	−0.185	−0.456	
	(0.455)	(0.246)	(0.443)	[0.324]
	(0.364)	(0.370)	(0.611)	[0.459]
Insurance, carriers and related activities	−1.310	−0.124	−1.435	
	(0.624)**	(0.595)	(0.837)*	[0.112]
	(0.539)**	(0.513)	(0.684)**	[0.041]
Securities, commodity contracts, and investments	−0.310	−0.167	−0.477	
	(0.574)	(0.611)	(1.012)	[0.646]
	(0.329)	(0.412)	(0.526)	[0.368]
Rental and leasing services, lessors of intangible assets	−0.035	−0.081	−0.116	
	(0.250)	(0.419)	(0.558)	[0.839]
	(0.292)	(0.334)	(0.487)	[0.813]
Funds, trusts, and other financial vehicles	0.984	−0.442	0.542	
	(1.067)	(1.156)	(1.175)	[0.653]
	(1.143)	(1.591)	(2.344)	[0.818]

Note: See notes to Table 4 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

lags (the first row), five lags (the second row), and one lag while excluding the lagged dependent variable, that is, lagged GSP growth (the last row). The results in this table are broadly consistent with those reported in Table 2, especially for the summer.

Autocorrelations of states' GDP growth rates. Table A5 reports the first-order autocorrelations of GDP growth rates for the entire cross section of U.S. states. Our results document that an overwhelming majority of states display a positive and statistically

TABLE A23

Robustness of Table 5 (Including 1-Year Lag of Temperature)

	Winter	Spring	Summer	Fall
North contemp.	0.276 (0.165)* (0.225)	0.063 (0.301) (0.170)	0.115 (0.268) (0.220)	−0.224 (0.236) (0.163)
North 1-year lag	0.263 (0.205) (0.162)	0.300 (0.196) (0.197)	−0.022 (0.306) (0.224)	0.114 (0.225) (0.242)
Sum of coefficients	0.539 (0.262)** (0.335)	0.363 (0.339) (0.244)	0.093 (0.333) (0.438)	−0.111 (0.257) (0.319)
Wald test's p-value	[0.045] [0.147]	[0.290] [0.175]	[0.781] [0.837]	[0.668] [0.738]
South contemp.	−0.102 (0.167) (0.092)	0.049 (0.138) (0.051)	−0.325 (0.173)* (0.087)***	0.549 (0.179)*** (0.054)***
South 1-year lag	0.009 (0.120) (0.082)	0.152 (0.182) (0.086)*	−0.390 (0.207)* (0.141)***	0.326 (0.187)* (0.111)***
Sum of coefficients	−0.092 (0.195) (0.069)	0.201 (0.211) (0.082)**	−0.715 (0.244)*** (0.182)***	0.876 (0.285)*** (0.147)***
Wald test's p-value	[0.638] [0.197]	[0.343] [0.026]	[0.005] [0.001]	[0.003] [0.000]
Midwest contemp.	−0.017 (0.084) (0.054)	−0.223 (0.140) (0.098)**	−0.003 (0.159) (0.069)	−0.162 (0.115) (0.078)**
Midwest 1-year lag	−0.126 (0.090) (0.060)**	0.243 (0.142)* (0.105)**	−0.154 (0.161) (0.131)	0.176 (0.115) (0.076)**
Sum of coefficients	−0.143 (0.119) (0.091)	0.020 (0.203) (0.113)	−0.157 (0.255) (0.116)	0.015 (0.157) (0.083)
Wald test's p-value	[0.235] [0.143]	[0.921] [0.861]	[0.540] [0.204]	[0.927] [0.864]
West contemp.	0.018 (0.096) (0.069)	−0.121 (0.149) (0.069)*	0.068 (0.147) (0.149)	−0.014 (0.168) (0.165)
West 1-year lag	0.057 (0.124) (0.072)	0.047 (0.162) (0.169)	−0.152 (0.149) (0.116)	−0.069 (0.150) (0.082)
Sum of coefficients	0.075 (0.165) (0.094)	−0.075 (0.253) (0.213)	−0.083 (0.221) (0.212)	−0.083 (0.249) (0.115)
Wald test's p-value	[0.650] [0.440]	[0.769] [0.732]	[0.708] [0.702]	[0.739] [0.482]

Note: See notes to Table 5 in the main text. Standard errors, first clustered by year and second clustered by state, are in parentheses.

TABLE A24

Robustness of Table 1 (Using Arellano–Bond)

	Whole year	Winter	Spring	Summer	Fall
Panel analysis	−0.026	−0.002	−0.049	−0.134	0.115
	(0.082)	(0.032)	(0.034)	(0.042)***	(0.056)**

Note: See notes to Table 1 in the main text. Robust standard errors are in parentheses.

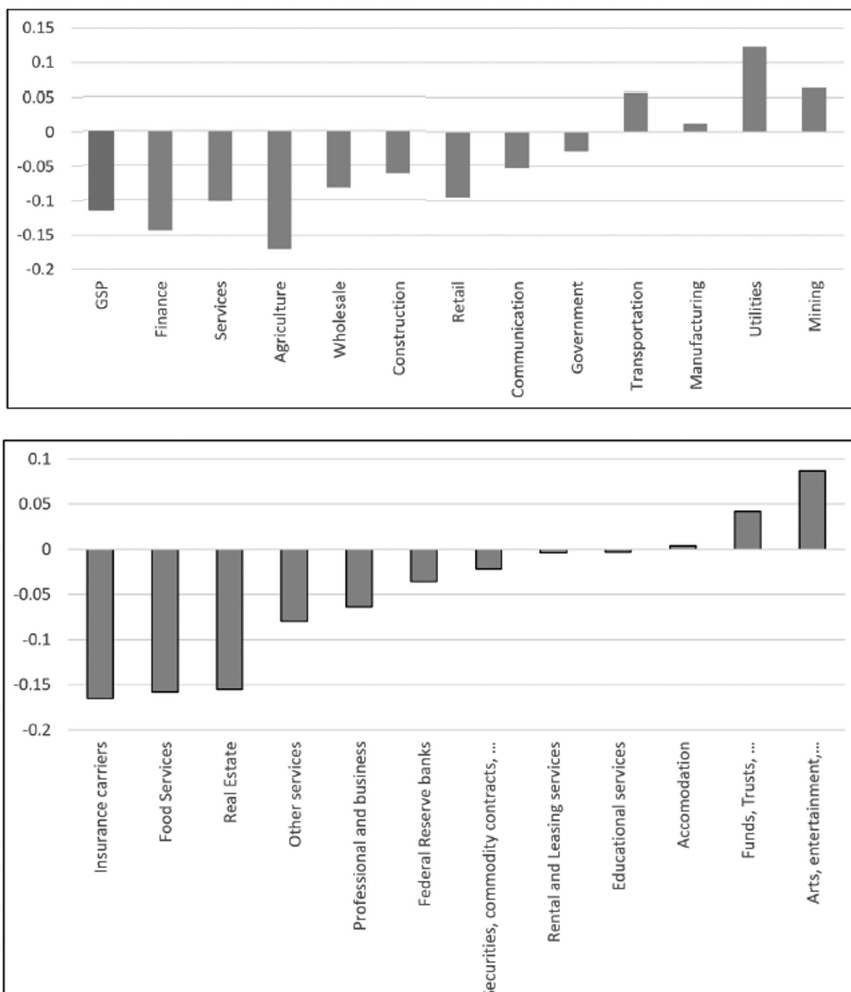

Fig. A1. Standardized Regression Coefficients for the Industry Analysis Reported in Table 4.

TABLE A25

Robustness of Table 2 (Using Arellano–Bond)

	Winter	Spring	Summer	Fall
Contemporaneous temp.	−0.020	−0.059	−0.191	0.143
	(0.034)	(0.030)*	(0.043)***	(0.054)***
One-year lagged temp.	0.012	0.083	−0.137	0.126
	(0.027)	(0.048)*	(0.055)**	(0.040)***
Sum of coefficients	−0.008	0.024	−0.328	0.270
	(0.043)	(0.052)	(0.075)***	(0.083)***
Wald test's p-value	[0.860]	[0.651]	[0.000]	[0.002]

Note: See notes to Table 2 in the main text. Robust standard errors are in parentheses.

TABLE A26

Robustness of Table 3 (Using Arellano–Bond)

	Winter	Spring	Summer	Fall
Productivity	−0.011	0.002	−0.152	0.142
	(0.050)	(0.052)	(0.065)**	(0.059)**
Employment	−0.004	−0.068	0.048	−0.012
	(0.016)	(0.032)**	(0.036)	(0.021)

Note: See notes to Table 3 in the main text. Robust standard errors are in parentheses.

significant first-order autocorrelation. We use this finding to motivate the inclusion of the lagged dependent variable in our baseline empirical specification.

Correlations of seasonal temperatures. Table A6 reports the correlations of seasonal temperatures in the cross section of U.S. states. The median values of correlations provided in the table are typically positive and very low. The only correlation for which we cannot reject the null hypothesis of null correlation at the 90% confidence level is the one between spring and summer average temperatures. The correlations between fall and summer temperatures, which are the seasons that are the main focus of attention, are very modest and indistinguishable from zero in the cross section of states. This finding supports the claim that the results presented are not affected by multicollinearity.

Standardized industry regressions. In Figure A1, we report the results obtained by standardizing the growth rate of GDP of each industry and the summer temperatures by their respective average volatilities. The specification is identical to the one used in the main text for this part of the analysis. The figure shows that a one standard deviation increase in summer temperature results in a change in the growth of GDP between −0.2 and +0.2 standard deviations, depending on the specific industry under consideration.

TABLE A27

Robustness of Table 4 (Using Arellano–Bond)

	Pre-1997	Post-1997	Avg. GDP share (%)
Gross state product	−0.164 (0.061)***	−0.236 (0.067)***	100
Services†	0.110 (0.046)**	−0.165 (0.076)**	25.7
Finance, insurance, real estate	−0.137 (0.227)	−0.505 (0.179)***	20.5
Manufacturing	−0.052 (0.148)	0.344 (0.512)	12.9
Government	−0.101 (0.057)*	−0.011 (0.104)	12.2
Retail	−0.011 (0.075)	−0.122 (0.108)	6.6
Wholesale	−0.136 (0.081)*	−0.267 (0.165)	5.9
Communication/Information†	−0.223 (0.135)*	−0.066 (0.423)	4.5
Construction	−0.038 (0.148)	−0.218 (0.226)	4.4
Transportation	0.243 (0.287)	0.131 (0.114)	3.0
Utilities	0.454 (0.202)**	0.129 (0.340)	1.8
Mining	−0.110 (0.526)	0.272 (0.324)	1.4
Agriculture, forestry, fishing	−3.054 (0.486)***	−2.456 (0.690)***	1.1

Note: See notes to Table 4 in the main text. Robust standard errors are in parentheses.

Inclusion of additional seasons in the industry regressions. In this section, we consider four additional specifications for the industry analysis presented in the main text. The first specification also includes the fall (for which the coefficient is sometimes significant in our total GSP regressions). The second specification includes the fall in addition to estimating a pooled coefficient for spring and winter (which are robustly insignificant in our analysis). The third specification includes all the seasons with separate coefficients and it is focused on the post-1990 sample. The fourth specification includes a separate coefficient for each season, estimated using the entire sample. The results presented in Figure A2 document that, despite some marginal loss of power, the estimated summer coefficients appear very much in line with those in our benchmark specification.

We note that the results for Case 3 and Case 4 in Figure A2 combine industry state-level data over the two subsamples that coincide with the adoption of NAICS codes

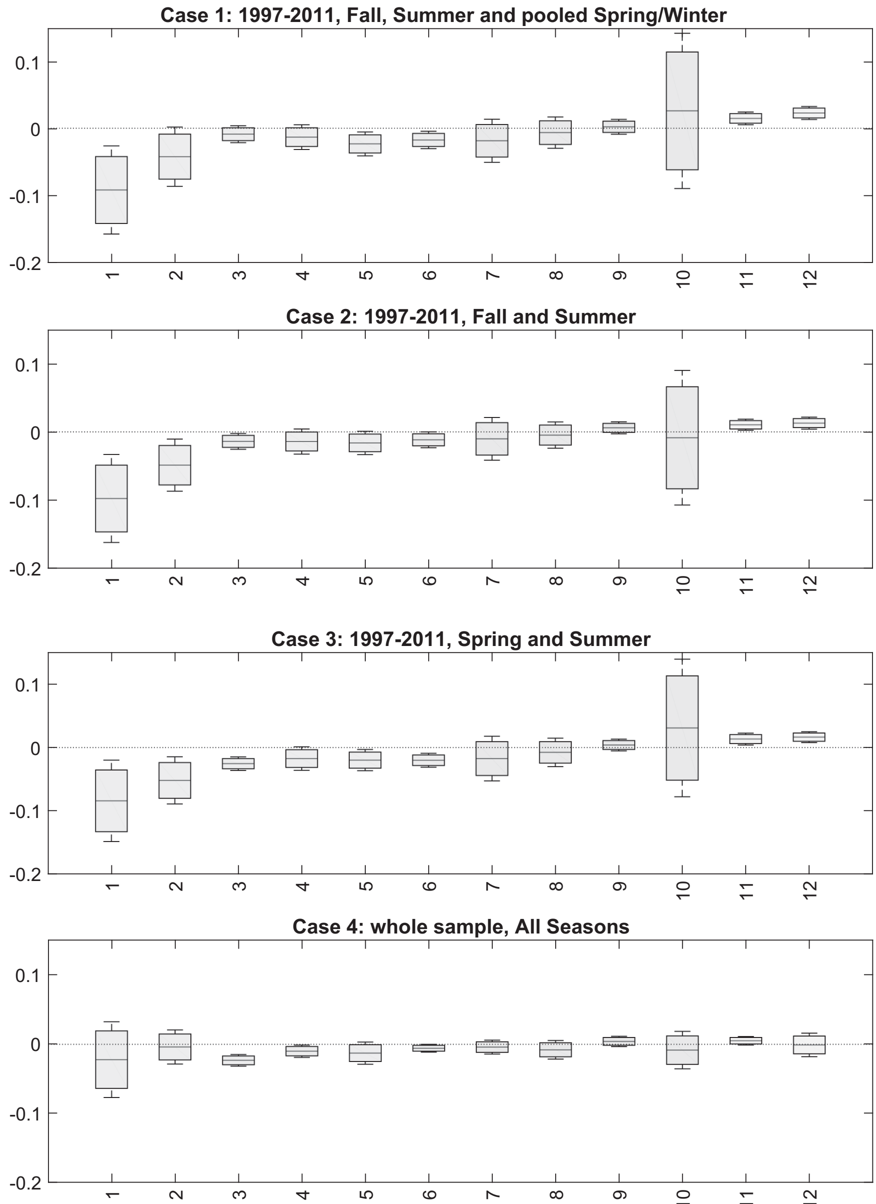

FIG. A2. Inclusion of Additional Seasons in the Industry Regressions Reported in Figure 1.

TABLE A28

ROBUSTNESS OF TABLE 4 (USING ARELLANO–BOND)

	Post-1997	Ave GDP share (%)
Services		
Professional and business services	−0.102	11.6
	(0.095)	
Educational services, health care, social assistance	−0.044	7.7
	(0.067)	
Other services, except government	−0.238	2.6
	(0.108)**	
Food services and drinking places	−0.339	2.0
	(0.152)**	
Arts, entertainment, and recreation	0.513	1.0
	(0.194)***	
Accommodation	0.219	0.9
	(0.273)	
Finance, insurance, real estate		
Real estate	−0.640	11.4
	(0.134)***	
Federal Reserve banks, credit intermediation, and related services	−0.181	3.6
	(0.304)	
Insurance, carriers and related activities	−1.637	2.6
	(0.673)**	
Securities, commodity contracts, and investments	0.309	1.3
	(0.376)	
Rental and leasing services, lessors of intangible assets	0.149	1.3
	(0.320)	
Funds, trusts, and other financial vehicles	1.176	0.2
	(0.847)	

NOTE: See notes to Table 4 in the main text. Robust standard errors are in parentheses.

TABLE A29

ROBUSTNESS OF TABLE 5 (USING ARELLANO–BOND)

	Winter	Spring	Summer	Fall
North	0.322	0.079	0.205	−0.236
	(0.248)	(0.194)	(0.225)	(0.168)
South	−0.115	0.148	−0.257	0.672
	(0.096)	(0.136)	(0.096)***	(0.069)***
Midwest	−0.010	−0.156	0.028	−0.108
	(0.059)	(0.103)	(0.076)	(0.084)
West	−0.029	−0.087	0.053	0.002
	(0.069)	(0.070)	(0.178)	(0.174)

NOTE: See notes to Table 5 in the main text. Robust standard errors are in parentheses.

(i.e., pre- and post-1997). The results should therefore be interpreted with caution in light with the following note reported on the BEA website:[19]

19. Available at https://www.bea.gov/regional/docs/product/. Additional details on the industry changes that took place when NAICS codes were introduced are available at https://www.naics.com/history-naics-code/.

> "**Cautionary note**:
> There is a discontinuity in the GDP-by-state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. [. . .] This data discontinuity may affect both the levels and the growth rates of GDP by state. Users of GDP by state are strongly cautioned against appending the two data series in an attempt to construct a single time series for 1963 to 2017."

A.6 Further Robustness Checks

Gridded temperature data set. In this section, we show that our results are robust to using temperature data that are not deseasonalized. We reestimate our results in Tables 1–6 using gridded temperature data from the NOAA nClimDiv data set.[20] The results are reported in Tables A7–A12. Throughout for brevity, we only report two standard errors, clustered by year and clustered by state.

Temperature aggregated by population data. In this section, we show that our results are robust to using a temperature data set in which weather station data are aggregated to the state level using county population instead of county area. We reestimate our results in Tables 1–6 using temperature data aggregated by population. The results are reported in Tables A13–A18.

Including 1-year lagged temperatures. In this section, we show that our results are robust to including the 1-year lag of temperature in all specifications. We reestimate our results in Tables 3–6 including the 1-year lag of seasonal temperature variables. The results are reported in Tables A19–A23.

Arellano–Bond estimator. In this section, we show that our results in Tables 1–6 are robust to using GMM estimators developed by Arellano and Bond (1991) that produce consistent estimates of a dynamic panel for finite T. We use first differences with respect to time. Because T is fairly large, using all possible instruments could lead to a bias of "too many instruments" (Newey and Windmeijer 2009), so we restrict the number of instruments and use one-step GMM estimators with a naive weighting matrix. These estimators remain consistent when T (the number of time periods) and N (the number of states) and the number of instruments are large (Alvarez and Arellano 2003). We use lags 2–10 as instruments, use small sample adjustments, and estimate robust standard errors. The results are reported in Tables A24–A29.

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