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Research article

Revisiting the temperature-economic growth relationship using global subnational data

Xiaobing Zhao[a,*], Mason Gerety[a], Nicolai V. Kuminoff[b]

[a] *The W. A. Franke College of Business, Northern Arizona University, 20 W. McConnell Drive, NAU Box 15066 Flagstaff, AZ 86011-5066, USA*
[b] *Department of Economics, Arizona State University and NBER, Main Campus, PO BOX 879801, Tempe, AZ 85287-9801, USA*

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ABSTRACT

Previous studies have used national data to demonstrate that higher annual temperatures negatively affect economic output and growth. Yet, annual temperatures and productivity can also vary greatly across space *within* countries. With this in mind, we revisit the relationship between temperature and economic growth using *subnational* short panel data for 10,597 grid cells across the terrestrial Earth. Our estimates from fitting a quadratic model to the data imply that cell-level economic growth in countries with below-median per-capita incomes is concave in temperature, with a maximum at about 16 °C. Our findings suggest that even with similar economic development within a country, climate vulnerability can vary at the regional level. Furthermore, as soon as we take into account the nonlinear relationship between temperatures and economic growth within countries, the impacts of temperature increases are found to be larger, compared to those that disregard such within-country heterogeneity.

> *"Put a man into a close warm place …and he will feel great faintness. If under this circumstance you propose a bold enterprise to him, I believe you will find him very little disposed towards it…"*
>
> Montesquieu, 1748.

1. Introduction

Prior evidence on the role of climate in economic development suggests negative linear impacts of temperature on not only income but also economic growth, *particularly in poor countries*. For instance, Schlenker, Hanemann, and Fisher (2004) document a reduction in agricultural output with increases in temperature for counties east of the 100th meridian; Hsiang (2010) finds that positive temperature shocks have negative effects on income in Caribbean-basin countries during the hottest season—a 1 °C warming decreases income by 2.5 percent; and Dell et al. (2012) [henceforth DJO] find that higher temperatures substantially reduce economic growth (not just the level of income) in poor countries, but not in rich countries.[1]

There is also growing evidence that the effects of temperature on income and economic growth are *nonlinear*.[2] For example, using county-level data for the United States, Graff Zivin and Neidell (2014) show that temperature increases at the higher end of the distribution reduce labor productivity in industries with high exposure to weather such as agriculture, forestry, fishing, and hunting; mining; construction; transportation and utilities; and manufacturing. Similarly, Deryugina and Hsiang (2014) find nonlinear effects of daily temperature on annual personal income per capita in the United States: at colder temperatures, an increase in temperature increases income, but it decreases income at temperatures above 15 °C. Burke, Hsiang, and Miguel (2015) [henceforth BHM] document global nonlinear effects of temperature on economic growth for 166 countries. They find country-level economic growth is concave in temperature with a maximum at 13 °C. However, BHM find that rich countries are not statistically distinguishable from poor countries in terms of the temperature-economic growth relationship. This is somewhat counterintuitive, as one might expect rich countries to have greater access to infrastructure needed to adapt to higher temperatures, for example.

Importantly, previous studies (e.g., DJO, BHM) typically use national data. Nations are arguably natural units of aggregation for tracking economic activity. However, this is not true for climatic and geophysical variables, such as temperature and precipitation. As Nordhaus (2006) observes, "for many countries, averages of most geographic variables (such as temperature or distance from seacoast) cover such a huge area that they are virtually meaningless" (p. 3511).

* Corresponding author.
E-mail addresses: xiaobing.zhao@nau.edu (X. Zhao), Mason.Gerety@nau.edu (M. Gerety), kuminoff@asu.edu (N.V. Kuminoff).

[1] See also Nordhaus (2006), Dell et al. (2009), Ng and Zhao (2011), Balvers et al. (2017), and Du and Zhao (2017) among others.
[2] "Nonlinear" in this paper is in terms of variables not parameters.

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Moreover, if the subnational relationship between temperature and economic activity is nonlinear, then Jensen's inequality implies that the impact estimate based on the national relationship will be biased (i.e., the impact at the average national temperature is a biased estimate of the average impact across the country).

With this in mind, we revisit the international within-country relationship between temperature and economic growth using 1-degree longitude by 1-degree latitude grid cell data for the terrestrial Earth. The data, originally developed by Nordhaus (2006), describe temperature and gross cell product (GCP) for 190 countries in 1990, 1995, 2000, and 2005. Increasing spatial resolution to the grid cell level improves statistical precision, makes temperature measures more meaningful, and tightens the spatial link between temperature and economic growth. Using long-horizon data measured at five-year intervals may also better account for adaptation over long run.

Empirically, we find strong evidence of a nonlinear relationship between temperature and economic growth at the cell level, with stronger effects in poorer countries. Our estimates from fitting a quadratic model to the data imply that cell-level economic growth in countries with below-median per-capita incomes is concave in temperature, with a maximum at about 16 °C. Our findings suggest that even with similar economic development within a country, climate vulnerability can vary at the regional level, depending on the regional temperature. Furthermore, as soon as we take into account the nonlinear relationship between temperatures and economic growth within countries, the impacts of temperature increases are found to be larger, compared to those that disregard such within-country heterogeneity, supporting more aggressive global climate policy.

Our paper contributes to the literature on economic growth. Economists have found that economic growth depends on population growth, physical capital, human capital, political stability, strength of institutions, economic convergence, ideas, education, financial development, and etc. (e.g., Romer, 1990; Barro, 1991; Mankiw et al., 1992; King and Levine, 1993; Acemoglu et al., 2001; Barro and Lee, 2013; Acemoglu and Johnson, 2014; Squicciarini and Voigtländer, 2015; Hanushek et al., 2017). We add to the extant studies by focusing the impact of temperature on economic growth, particularly its interaction with economic development. Our results suggest that climate vulnerability in poor countries is also region dependent.

In this paper, we use GCP, the cell-level variant of GDP, as our measure of economic progress. It is important to point out that GDP/GCP is but one measure of economic productivity and does not account for environmental externalities such as pollution and income inequality, which may be important to policymakers. Therefore, we call for future research to explore the relationship between temperature and alternative measures of economic well-being.

2. Data

To the best of our knowledge, the most comprehensive subnational data currently available are contained within the G-Econ database developed by Nordhaus (2006). It divides the terrestrial Earth into a grid with 25,572 cells measuring 1-degree latitude by 1-degree longitude and provides estimates for each cell's economic production, gross cell product (GCP), temperature, precipitation, population, and other important demographic and geophysical variables. These data are available for 1990, 1995, 2000, and 2005.[3] Table 1 shows summary statistics for the G-Econ data used in our estimation. While our sample period (1990–2005) is shorter than that of DJO (1950–2003) and sparser in the temporal dimension (quinquennial as opposed to annual data), our sample size is larger by an order of magnitude. There are at least three other important differences between our data and the data sets used by prior studies.

First, Deryugina and Hsiang (2014) also use subnational variation in weather, but their study is limited to the United States. A priori, there is no reason to believe that results for the United States generalize to the rest of the world. Furthermore, the US data alone cannot be used to determine whether poor countries are more vulnerable to warming. Second, whereas DJO and Deryugina and Hsiang (2014) both use annual data, the G-Econ data that we use are only available at five-year intervals. An advantage of using longer-horizon data is to better account for adaptation over long run. Finally, while Deryugina and Hsiang (2014) and Hsiang (2010) focus on the level of income, we follow DJO to focus on income growth. Focusing on longer-run growth allows us to acknowledge the roles of mitigation and adaptation. Further, since growth effects compound over time, even small growth effects can accumulate into large income effects.

[3] 1990 was chosen as the base year to reflect changes in national boundaries that resulted from the breakup of the Soviet Union. To give a sense of scale, the average cell in the United States contains 2.3 counties.

3. Empirical model

BHM document an inverted U-shaped relationship between temperature and economic growth. Therefore, our baseline econometric model is a quadratic specification of temperature and economic growth:

$$g_{i,t} = c_i + y_t + \beta_1(Poor_i \times T_{i,t}) + \beta_2(Poor_i \times T_{i,t}^2) + \beta_3(Rich_i \times T_{i,t}) + \beta_4(Rich_i \times T_{i,t}^2) + \sum_k \gamma_k X_{i,t}^k + \varepsilon_{i,t} \quad (1)$$

where $g_{i,t}$ is the five-year growth rate in per capita GCP in grid cell i. It is measured as a first difference in the natural log of quinquennial per capita GCP. Among the control variables, c_i is a cell fixed effect, y_t is a time fixed effect (interacted separately with a dummy for whether a country is "poor" and dummies for six global regions),[4] $T_{i,t}$ is five-year average temperature, $Poor_i$ is a dummy for a country having below-median per-capita income in the first year the country enters the dataset, $Rich_i$ is a dummy for a country having above-median per-capita income in the first year the country enters the dataset, and X is a vector of additional economic and geographic controls: population growth and precipitation. Importantly, the time-invariant cell fixed effect c_i, will absorb all location-specific constants (e.g., differences in institutions), forcing the identification to come from variation within a given cell over time. DJO also include lagged temperature as an explanatory variable. Since we use long-horizon data, we exclude temperature lags. Following DJO, standard errors are clustered by country and region-year to allow for not only spatially correlated economic shocks caused by national or subnational policies and trade but also arbitrary correlation within region-years.

This paper also explores alternative specifications (i.e., a cubic polynomial and a linear spline). The results in Section 4.3 suggest that the quadratic specification captures the empirical relationship between temperature and economic growth at the cell level in our sample.

4. Empirical results

4.1. Regression results using country-level data

As a benchmark for comparison, we start by reproducing the main specification from DJO.[5] The results based on their original country-level data are reported in Section "DJO" of Table 2. The first column of Table 2 replicates column (1) of their Table 3. It includes country fixed effects, region × year fixed effects for six global regions, and poor

[4] In other words, all of our model specifications include region × year fixed effects and poor country × year fixed effects. Six global regions by DJO are Middle East/North Africa, sub-Saharan Africa, Latin America and Caribbean, Western Europe and offshoots, Eastern Europe and Central Asia, and Asia and Pacific Islands (p. 74).

[5] Their data can be downloaded from the *American Economic Journal: Macroeconomics* website. We use Stata to conduct all the empirical tests in this paper.