GDP and Temperature: Evidence on Cross-Country Response Heterogeneity*

Kimberly A. Berg† Miami University

Chadwick C. Curtis‡ University of Richmond

Nelson C. Mark§ University of Notre Dame and NBER.

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Abstract

We use local projections to estimate the cross-country distribution of impulse responses of real GDP per capita growth to temperature shocks. Negative growth responses are found for six of the Group of Seven countries (Canada being the exception) while positive responses are found for four of the nine poorest countries. Temperature shocks have adverse effects on growth for 42 countries and have positive effects for 52 countries. Negative level effects are found for 34 countries and positive level effects for 13 countries. After controlling for latitude, the growth impulse responses are decreasing in average real GDP per capita and in long-term growth. Counterfactual projections under a high-emissions scenario show temperature induced losses in year 2100 of 1.9 percent ($4,837 2017 dollars) of real GDP per capita for the United States.

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†Title: Assistant Professor. E-mail address: bergka@miamioh.edu. Phone: 513-529-3819. Mailing address: Miami University, 2054 Farmer School of Business, 800 East High Street, Oxford, OH 45056.

‡Title: Associate Professor. E-mail address: ccurtis2@richmond.edu. Department of Economics, Robins School of Business, University of Richmond.

§Title: Alfred C. DeCrane Jr. Professor. E-mail address: nmark@nd.edu. Department of Economics, University of Notre Dame. NBER.

1 Introduction

This paper studies how temperature affects GDP and how the responses vary across countries. The response of real GDP per capita growth to temperature shocks are estimated by local projections (Jordà, 2005). We consider the role of a country's own temperature, and two components of country temperature: the global (common) component and the idiosyncratic component. We are also able to distinguish between growth and level effects from the various temperature shocks. We then study determinants of cross-country response variation in cross-sectional regressions of the local projection coefficients on country characteristics. Finally, we conduct a counter-factual analysis to obtain economic benefits and damages across countries resulting from global warming implied by our reduced form estimates.

Local projections present a flexible method for us to estimate the impulse response of real GDP per capita growth to temperature shocks while imposing few restrictions. Studies that employ panel regression impose extensive homogeneity restrictions across countries. Depending on the study, they find either uniformly negative effects of higher temperature on growth or negative effects only for poor countries. In contrast to panel regression studies, we estimate and study the entire cross-country response distribution. Our analysis finds that the impulse responses of rich country growth to temperature shocks are likely to be negative, while that of many poor countries are likely to be positive. Negative growth responses are found for six of the Group of Seven (G-7) countries (Canada being the exception). Positive responses are found for four of the nine poorest countries. Distinguishing between level and growth effects over the short-to-medium run, we find temperature shocks to have a significantly negative growth effect for 42 countries and a significantly positive growth effect for 52 countries. Negative level effects are found for 34 countries and positive level effects for 13 countries.

Perhaps, the natural measure of temperature is that which pertains to the country being examined. But, country temperature is relatively noisy, and it is also useful to examine its decomposition into a systematic global component and the unsystematic idiosyncratic component. The global component is conceptually attractive because it forms an association with climate change, which is a global phenomenon. The idiosyncratic component, on the other hand, shows similarities with the regressor in panel regressions with time-fixed effects. For some countries, we find the impulse responses of growth to global and idiosyncratic temperature shocks go in opposite directions. Qualitatively, rich country impulse responses appear to be driven more by shocks to global temperature than from the idiosyncratic component. The prominence of the global temperature component lends support to Bansal and Ochoa (2011)'s notion that temperature is a source of aggregate financial risk.

Having estimated country growth impulse responses, we next investigate the determinants of cross-country response variation in cross-sectional regressions of local projection temperature response coefficients on various country characteristics. This methodology draws on research strategies used in finance (e.g., Lustig and Richmond (2020) who regress the exchange rate's dollar-factor 'beta' on gravity variables). There is no 'generated regressor' problem in this cross-sectional analysis because the estimated response coefficients are the dependent variable. Our main findings here are, after controlling for latitude, the growth impulse response coefficients are decreasing in average real GDP per capita and decreasing in long-horizon growth. Finer structural distinctions across countries, such as average agricultural, industrial, and manufacturing shares of GDP, have only limited explanatory power.

We use our estimated local projection dynamics to perform reduced form counterfactual analyses and to construct empirical damage functions. This analysis gives a country-by-country assessment of economic damage or benefit resulting from projected global warming. Under the high-emissions SSP5-8.5 pathway, our estimates imply cumulative economic losses for most rich countries (U.S. (-1.9%), U.K. (-1.6 percent), Germany (-0.8%), Japan (-2.3%)) but confers benefits to large developing countries such as Brazil (5.3%), Nigeria (8.8%), China (9.6%), and India (5.7%). Of course, the historical relationship between real GDP per capita growth and temperature upon which this analysis is based, may not remain stable in the future resulting from adaptation or environmental tipping points. However, this qualification applies to all counterfactual and damage assessments based on historical estimates.

A central motivation for this project is to shed light on limited and conflicting conclusions in the literature regarding impact heterogeneity of temperature variation on GDP growth. Depending on the particular study, the empirical literature that employs panel regression, finds either an inverse relationship between temperature and GDP for all countries, or an inverse relationship that holds only for poor countries. A path-breaking study in this literature is Dell et al. (2012), who use international data in estimation with country and time-fixed effects. An important motive for their panel regression approach was to use country fixed effects to control for omitted-variables bias that was present in an earlier generation of studies of cross-sectional regressions of time-averaged GDP on temperature.[1] Dell et al. (2012) reports that increased temperature lowers GDP per capita growth, but only for poor countries. Leta and Tol (2019) and Henseler and Schumacher (2019) report similar results for total factor productivity growth. Burke et al. (2015), on the other hand, find increased temperature to have a negative effect on GDP growth but do not find differential impacts between rich and poor countries. Bansal and Ochoa (2011) find increasing global temperature lowers GDP growth of all countries with larger effects on low latitude countries.[2]

[1]The most prominent candidate omitted variables may be institutional quality, which is controlled for by the country fixed effect in panel regressions. Studies by Acemoglu et al. (2002), Easterly and Levine (2003), and Rodrik et al. (2004) argue institutions are main drivers of long-run growth outcomes.

[2]The panel regression approach to study the economic effects of climate was introduced by Deschênes and Greenstone (2007), who estimated the effect of temperature on agricultural profits in the United States. Also, focusing on the United States, Colacito et al. (2019) reports higher summer temperatures are damaging to output growth in southern states and the negative impacts are by geography, not income and Hsiang et al. (2017a), who examines growth in county-level income, similarly finds income is negatively impacted by temperature in the south

Our study differs from these panel-regression studies along three dimensions. First, our paper studies the growth responses to actual changes in country-specific temperature. Panel regressions with time-fixed effects estimate the response of the deviation of a country's growth from the global (cross-sectional) average to variation in the deviation of country temperature from the global average. The independent variable is thus a coarsely constructed idiosyncratic component of temperature variation while the response variable is a similarly blunt idiosyncratic component of real GDP per capita growth. Second, we examine growth responses to global and idiosyncratic temperature changes, whereas time-fixed effects in panel regressions remove the global component. Third, instead of imposing extensive homogeneity restrictions typical in panel regressions, we allow extensive response heterogeneity across countries.

Informed by the extant literature, our prior beliefs were that the time-series variation would reveal a distribution of local projection coefficients heavily weighted with negative values and the far left tail populated primarily by poor, low latitude countries. It was surprising to estimate the direction of growth responses to be roughly evenly split between positive and negative and to find the richer countries generally on the negative side of the distribution.

Some broader implications follow from this project. First, the pattern of cross-country response heterogeneity can supplement the ethical arguments presented by Stern (2008) to incentivize rich countries to invest in abatement strategies. The evidence that rich countries are directly economically damaged by warming should naturally incentive them to invest in climate mitigation.[3] Second, our results can provide refinements to damage function specifications in integrated assessment models (IAM) that compute welfare costs and evaluate the social cost of carbon. Since extant empirical literature finds higher temperatures to be more economically damaging to poorer and hotter regions, regional IAMs, informed by such empirical damage estimates produce similar regional damage projections.[4] The geographical variation provided by our country-specific assessments to the knowledge base can provide more detailed specifications of IAM damage functions. Additionally, IAM welfare and social cost of carbon calculations can be sensitive depending on whether temperature is assumed to affect GDP growth or only its level. Our estimates on which countries have experienced growth or level effects from temperature can also contribute to IAM damage function specification.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 discusses substantive ways our analysis departs from panel regression. The local projection analysis

and southwest, and increases in the north.

[3]In the absence of a global coordinated effort, Stern (2008) appeals to two ethical considerations to get the rich, industrialized countries to shoulder disproportionate costs of future abatement. First, industrialized countries are responsible for most of the current stock of greenhouse gasses and have gotten rich by generating those emissions. Second, poor countries are just beginning to overcome poverty through rapid growth and should not be forced to slow.

[4]DICE, FUND, and PAGE are prominent IAMs that serve as the main policy models employed by the U.S. Environmental Protection Agency. Regional IAMS have been developed by Hassler and Krusell (2012), Nordhaus and Yang (1996), Tol (2019), and Ricke et al. (2018), amongst others.

is reported in Section 4. Section 5 contains a robustness analysis. Section 6 undertakes the cross-sectional analysis. The counterfactual and empirical damage function analysis is in Section 7 and Section 8 concludes.

2 Data

Subsection 2.1 describes our data sources. Subsection 2.2 describes how we detrend and decompose country-level temperature into global and idiosyncratic temperature components.

2.1 Data Sources

Real GDP per capita is from the World Bank's, *World Development Indicators*. These data are valued in constant 2010 United States dollars and have a maximal span from 1960-2017. The empirical analysis uses only those 162 countries that have at least 20 consecutive years of observations. In the analysis of Section 6, we also use the World Bank's, *World Development Indicators* to represent country characteristics (GDP shares of agricultural, industry, and manufacturing).[5]

Our temperature observations are population-weighted by year and country. The source is *Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series (V 5.01)* Matsuura and Willmott (2018). This is a monthly dataset estimated from weather station records and interpolated to a 0.5-degree by 0.5-degree latitude/longitude grid. We aggregate the monthly data to annual observations by node. We overlay the temperature data with population data in 2000 from the *Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11* (Center for International Earth Science Information Network, 2018). The data provides population counts at a 2.5 minute by 2.5 minute latitude/longitude grid. We use the population weights to obtain population-weighted temperatures by country and year, which is the standard approach in the literature (Kahn et al. 2019 and Dell et al. 2012).[6]

2.2 Temperature

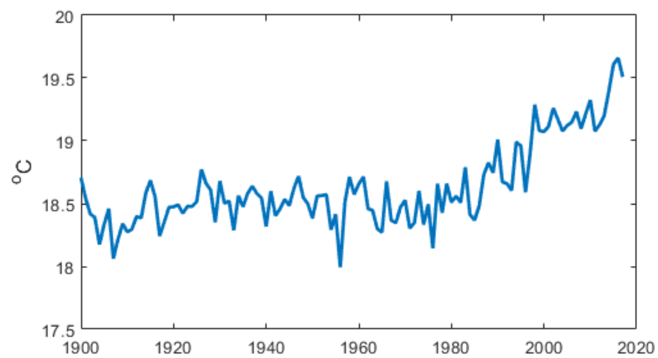
Temperatures, globally, are rising. Figure 1 shows the cross-sectional average of population-weighted country annual temperature from 1900-2017. This average annual temperature is seen to be reasonably stable from 1900 to 1980. After 1980, an upward trend is visually obvious, rising by about 1^{o}C over 40 years.

Our econometrics requires observations to be stationary. We induce stationarity by quadratically detrending population-weighted country annual temperature. Let $T_{j,t}$ be population-weighted

[5]The full list of countries and the available sample time period for each country are listed in Appendix A.

[6]We do not consider precipitation since earlier empirical work finds little or no effect of precipitation on income growth at the annual frequency.

Figure 1: Cross-Sectional Average of Population-Weighted Country Annual Temperature



country j temperature in year t, and let $\tau_{j,t}$ be quadratically detrended country temperature,

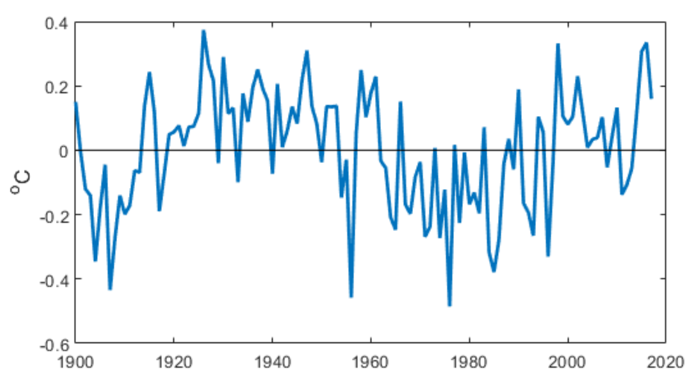
$$\tau_{j,t} = T_{j,t} - a_j - b_j t - c_j t^2,$$

where a_j, b_j, and c_j are ordinary least squares estimates. We then decompose detrended country temperature into a common global component and an idiosyncratic component. Global temperature (τ_t) is the cross-sectional average of $\tau_{j,t}$,

$$\tau_t = \frac{1}{N}\sum_{j=1}^{N} \tau_{j,t}.$$

Figure 2 shows the stationary representation of global temperature.[7]

Figure 2: Global Temperature



[7]Typically, the cross-sectional average is approximately the first principal component of the observations.

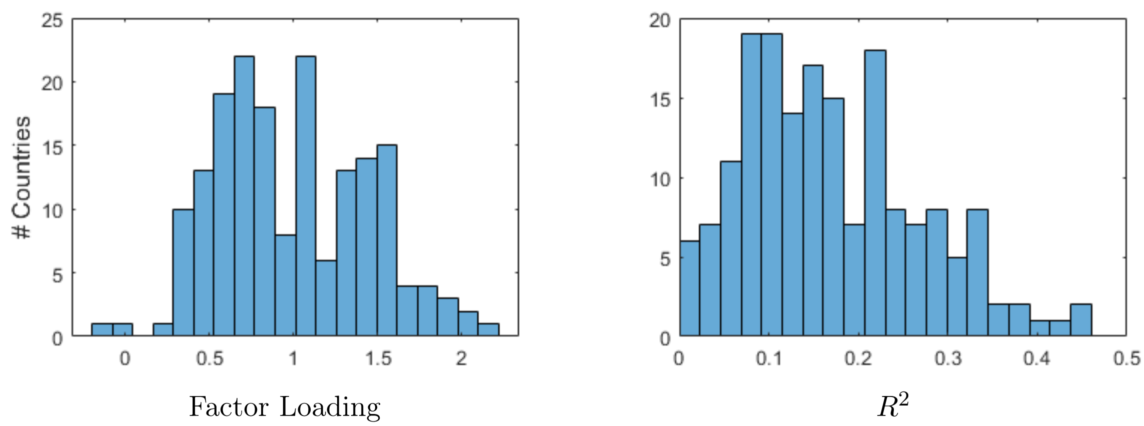
The idiosyncratic component, $\tau^o_{j,t}$, is the residual from regressing detrended country temperature $\tau_{j,t}$ on global temperature τ_t,

$$\tau^o_{j,t} = \tau_{j,t} - \delta_j \tau_t - \alpha_j, \tag{1}$$

where α_j is the country intercept and δ_j is the slope coefficient on τ_t. We refer to δ_j as the global temperature 'factor loading.'

Figure 3 displays histograms of the global temperature factor loadings and the R^2s from these country-specific regressions. The figures show a good deal of heterogeneity in the exposure of country temperatures to the global component. The R^2 distribution indicates that the importance of global temperatures in accounting for the variability in country-level temperature exhibits substantial heterogeneity across countries.

Figure 3: Slope Coefficients and R^2s from Regressing $\tau_{j,t}$ on τ_t.



We note that because the global and idiosyncratic temperature series are orthogonal to each other, they can be examined separately in the empirical analysis. We next discuss meaningful dimensions in which our analysis departs from the panel regression approach.

3 Departures from Panel Regression

The related literature widely adopts the panel regression estimation procedure with time-fixed effects to investigate the relationship between temperature changes and real GDP per capita growth (hereafter, *growth*).[8] Our analysis circumvents two features commonly associated with

[8] Kahn et al. (2019) is an exception, who estimate panel autoregressive-distributed lag models. They also find negative GDP growth impacts of temperature but no differences between rich and poor.

panel regressions. The first is the manner in which panel regression with time-fixed effects removes the global component from growth and temperature from estimation. The result is a regression of a coarsely constructed idiosyncratic growth variable on idiosyncratic temperature variation. The effects of actual country-level temperature variation are not observed. The second are the extensive homogeneity restrictions imposed on the slope coefficient of interest. While an objective of panel regression is to exploit cross-sectional variation to shrink standard errors, the imposition of extensive homogeneity should be imposed only when such restrictions are not rejected by the data. We address both of these issues in this paper by employing local projections (Jordà, 2005) for individual countries and pseudo panel local projections for limited groupings of similarly responsed countries.

3.1 Time Fixed Effects

To illustrate the 'behind-the-scene' data manipulations associated with time-fixed effects, let $y_{j,t}$ be log real GDP per capita of country $j = 1, \ldots, N$ in time t. Without loss of generality, we abstract from time-invariant country-fixed effects. Consider the panel regression of growth, $\Delta y_{j,t} = y_{j,t} - y_{j,t-1}$, on the country's annual temperature, $T_{j,t}$ with time fixed effects, θ_t,

$$\Delta y_{j,t} = \theta_t + \beta T_{j,t} + \epsilon_{j,t}. \tag{2}$$

Taking the cross-sectional average of equation (2) gives

$$\frac{1}{N}\sum_{j=1}^{N} \Delta y_{j,t} = \theta_t + \beta \frac{1}{N}\sum_{j=1}^{N} T_{j,t} + \frac{1}{N}\sum_{j=1}^{N} \epsilon_{j,t}. \tag{3}$$

Subtracting equation (3) from equation (2) elimates the time-fixed effect giving,

$$\Delta y_{j,t} - \frac{1}{N}\sum_{j=1}^{N} \Delta y_{j,t} = \beta \left(T_{j,t} - \frac{1}{N}\sum_{j=1}^{N} T_{j,t} \right) + \left(\epsilon_{j,t} - \frac{1}{N}\sum_{j=1}^{N} \epsilon_{j,t} \right). \tag{4}$$

The variables in equation (4) are deviations from the global average which amounts to coarsely constructed idiosyncratic components of growth and temperature. Running the panel regression with time-fixed effects, equation (2), is equivalent to running stacked least squares on equation (4).[9] Hence, the coefficient of interest in equation (4), β, is not an estimate of the growth response to variations in the country's temperature, but is an estimate of the relative (to the world) growth response to relative (to the world) variations in temperature. Since the variables are relative to the global average, a negative panel estimate of β tells us of a lower than average growth response

[9]See Appendix B for reporting on how, using our data, estimates from panel regression with country and time-fixed effects are nearly identical to stacked least-squares estimates with variables as deviations from their cross-sectional average.

but we are not certain this is evidence of a negative growth response. Similarly, the intervention is not an increase in local temperature, but is of local temperature relative to the global average, which could increase as a result of higher local temperature or lower world temperature.

3.2 Extensive Homogeneity Restrictions

In panel regression, the constrained slope is a weighted average of individual ordinary least squares estimates with weights related to country $j's$ share of the sample's temperature variation. Modest amounts of heterogeneity can and has been allowed with dummy variable interactions on the slope for broad classes of countries (e.g., above and below median income). If one's interest is to obtain a weighted average of individual country responses (or responses from broad subgroups), then the panel regression delivers the appropriate estimate. But if one's interest is to study individual country response, constrained (pooled) estimation should not proceed if the homogeneity restrictions are rejected.

As a precursor to our main empirical work, we test the extensive homogeneity restrictions that might typically be imposed in panel regression. Let $\tau^f_{j,t}$ be the notational 'stand-in' for any one of the three temperature measures $\tau^f_{j,t} \in \{\tau_{j,t}, \tau_t, \tau^o_{j,t}\}$. Consider the regression of growth on temperature,

$$100\Delta y_{j,t} = \beta_j \tau^f_{j,t} + x'_{j,t}\gamma_j + \epsilon_{j,t}, \tag{5}$$

where $x'_{j,t}\gamma_j = \sum_{k=1}^{2} \delta_{j,k}\Delta y_{j,t-k} + c_j$ are controls consisting of two lags of annual real GDP per capita growth and the regression constant. We test the homogeneity restrictions as follows. First, estimate equation (5) separately for each country, then sort countries into two groups: those whose $\hat{\beta}$s are positive and those whose are negative. Second, for each group, separately estimate the constrained version of equation (5) where $\beta_j = \beta$, for all j. Only the slope on temperature is constrained to be equal across countries. Let the slope in the positive beta group be β_p and for the negative beta group, β_n. A Wald test of the hypothesis $\beta_p = \beta_n$ is χ^2_1 under the null, and provides a test of the homogeneity restrictions.

Panel A of Table 1 shows the results using all countries in the sample. The growth response variation to changes in temperature is widespread and significant. Of the 162 countries, 86 of the slope point estimates are positive in regressions with country temperature, 65 with global temperature and 66 with idiosyncratic temperature. The extensive (i.e., across large numbers of countries) homogeneity restrictions are rejected by the data, as the p-values of the test statistic is 0 for each of the temperature measures.

Next, we report that the split between positive and negative betas is not simply a split between rich and poor countries. In panel B, the test is applied only to poor countries–those whose average real GDP per capita over the sample is below the median. Even among poor countries, many have positive growth responses to each of the temperature measures. Of the 81 poor countries, 35 of the slope point estimates are positive in regressions with country temperature, 49 with global

Table 1: Tests of Extensive Homogeneity Restrictions

	β_p	t-ratio	β_n	t-ratio	$\beta_p = \beta_n$	p-val
A. All Countries						
Country	1.273	6.110	-1.273	-7.218	87.003	0
Global	2.735	5.496	-2.861	-6.065	66.611	0
Idiosyncratic	1.201	5.548	-1.453	-7.350	81.959	0
B. Poor Countries						
Country	1.807	5.052	-1.542	-5.303	52.790	0
Global	2.923	4.527	-2.854	-3.661	32.566	0
Idiosyncratic	1.589	4.130	-1.793	-5.602	45.662	0

Notes: The slope is β_p in the positive beta group and is β_n in the negative beta group. A Wald test of the hypothesis $\beta_p = \beta_n$ is χ^2_1 under the null. Country temperature is $\tau_{j,t}$, global temperature is τ_t, and idiosyncratic temperature is $\tau^o_{j,t}$. Poor countries are those whose average real GDP per capita over the sample is below the median.

temperature, and 31 with idiosyncratic temperature. The estimated β_p is positive and highly significant. Here as well, the test of the homogeneity restrictions across poor countries is rejected.

The rejections of the homogeneity restrictions shown in Table 1 yields evidence that extensive pooling is not appropriate and the presence of widespread response heterogeneity, even among poor countries. The next section discusses our empirical methodology in more detail and presents the associated empirical results.

4 Impulse Responses by Local Projections

This section first discusses our local projection specification. We also discuss how estimation with limited pooling of small groups of countries with quantitatively similar responses can preserve the individual point estimates while achieving shrinkage in standard errors. Subsection 4.2 presents the impulse responses of real GDP per capita growth to country temperature shocks. Subsection 4.3 presents the results for global and idiosyncratic temperature shocks. Subsection 4.4 reports on an analysis that distinguishes between level and growth effects resulting from temperature shocks.

4.1 Local-Projection by Regression and Limited Scale Pseudo-Panel Estimation

Our local projections are the sequence of regressions at horizons $h \in \{0, ..., 7\}$ estimated separately for each country $j \in \{1, ..., 162\}$,

$$100\,(y_{j,t+h} - y_{j,t-1}) = \beta_{j,h}\tau^f_{j,t} + x'_{j,t}\gamma_{j,h} + \epsilon_{j,t+h}, \tag{6}$$

where $y_{j,t}$ is log real GDP per capita of country j at time t, $\tau^f_{j,t} \in \{\tau_{j,t}, \tau_t, \tau^o_{j,t}\}$ is the temperature measure under consideration, and $x'_{j,t}\gamma_{j,h} = \sum_{k=1}^{2} \delta_{j,h,k}\Delta y_{j,t-k} + c_{j,h}$ are controls consisting of two lags of annual real GDP per capita growth and the regression constant. The sample length for our countries ranges from 20 to 57 annual observations. The coefficient of interest is $\beta_{j,h}$, which measures the percent change in real GDP per capita from time $t-1$ to $t+h$ due to a $1^{o}C$ shock in the temperature variable at time t. As shown by Jordà (2005) and Plagborg-Møller and Wolf (2021), the local-projection coefficients are asymptotically equivalent to the impulse response function from a vector autoregression. Since impulse responses from vector autoregressions are colloquially referred to as responses to 'shocks,' we similarly refer to local projection estimates as growth responses to temperature 'shocks' even though the regressor is a temperature variable $\tau^{f}_{j,t}$ (and not a 'shock' *per se*). To further economize on terminology, we refer to these response coefficients as 'local-projection betas.' At horizons $h > 0$, the overlapping dependent variable observations induce serial correlation in the error terms which we address with Newey and West (1987) standard errors.

Limited Scale Pseudo-Panel Estimation. While extensive pooling was shown to be unjustified, limited pooling of countries with similar sized betas is supported by the data (reported in the next subsection). We supplement the local projection estimates with joint, constrained estimates from small sets of pseudo-panels of countries with similar sized local projection betas. By grouping locally similar countries, the point estimates from pseudo-panels remain close to the local-projection point estimates while achieving reductions in the standard errors.

Joint pseudo-panel estimation proceeds as follows. For a given horizon h, sort countries by their local-projection betas, then form groups of four countries. For each four-equation system, estimate the constrained beta specification,

$$100\left(y_{j,t+h} - y_{j,t-1}\right) = \beta_h \tau^{f}_{j,t} + x'_{j,t}\gamma_{j,h} + \epsilon_{j,t+h}, \tag{7}$$

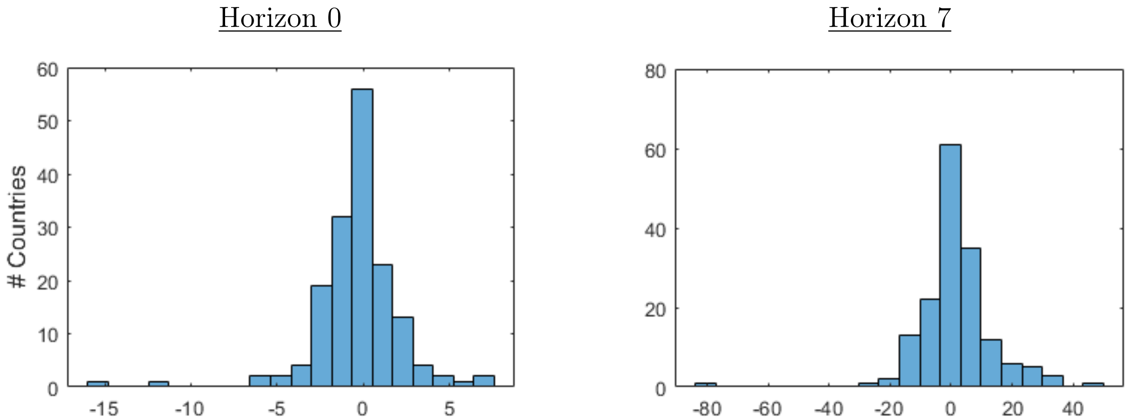
where only the local-projection beta is constrained to be equal within the group. The group membership can change from one horizon to the next, which is why we refer to these systems as *pseudo* panels. Estimate each pseudo-panel by generalized method of moments (GMM), with the regressors for the country j equation serve as instruments for that equation. This resembles a system of constrained least squares estimates but with GMM (system-wide Newey-West) standard errors. As a matter of terminology, we refer to these local-projection impulse response coefficients as 'pseudo-panel local-projection betas.'

4.2 Local Projections with Country Temperature

Our first results are for the responses of growth to country temperature shocks. The full set of 162 impulse response graphs are relegated to Appendix C, Figure C1. Here, in the main text, we report various summaries of the results.

Figure 4 displays the histograms of the country temperature local-projection betas (in percent)

Figure 4: Country Temperature Local-Projection Betas



Notes: Distribution of country temperature local-projection betas, $\beta_{j,h}$ from equation (6) for $j = 1, ..., 162$ and $h = 0$ and $h = 7$.

at horizons 0 and 7. These represent the percent growth impulse responses to a 1^oC country temperature shock. For each horizon, it can be seen that there are many positive and negative values, reflecting the wide dispersion of observed responses.[10]

Table 2: Country Temperature Local Projection and Pseudo Panel Local Projection Summary

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	96	90	88	86	83	80	76	77	98	90	86	86	86	78	74	74
# pos	66	72	74	76	79	82	86	85	64	72	76	76	76	84	88	88
# sig neg	8	12	16	15	10	13	8	8	58	58	58	46	62	46	54	42
# sig pos	8	5	6	8	9	11	12	13	36	36	40	40	40	44	52	52

Notes: This table shows the count of country temperature local-projection (estimates from equation (6)) and pseudo-panel local-projection (estimates from equation (7)) betas that are negative (neg), positive (pos), and statistically significant at the 5 percent level (sig neg and sig pos).

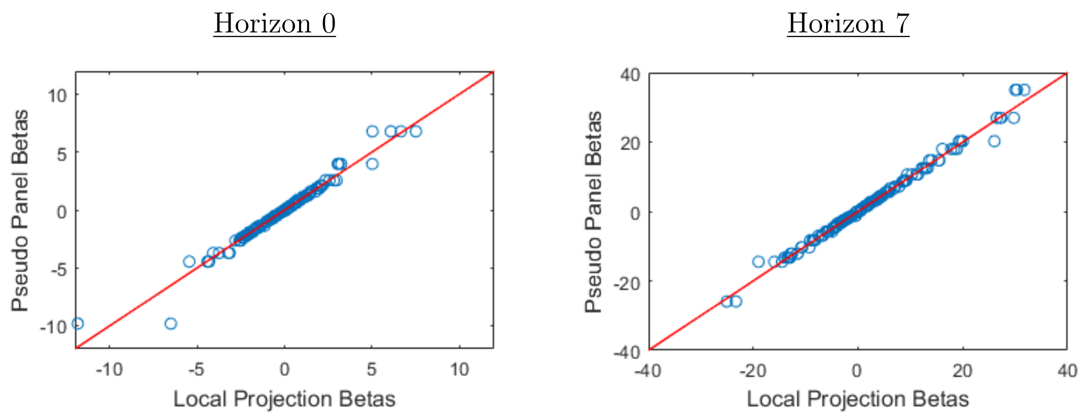
Table 2 reports a summary comparison between country temperature local-projection and pseudo-panel local-projection betas. This table lists the count of positive and negative betas and the count of the statistically significant positive and negative betas at the 5 percent level across horizons. At the shorter horizons, the count of negative coefficients exceeds the positives, but this reverses in the medium run (after 5 years). Comparing between the estimation methods at each horizon, the number of positive and negative coefficients is nearly identical. The primary

[10]Some of the responses are quite large in magnitude because the responses are for a 1^oC increase in country temperature, which is much larger than the normal variation in observed temperature.

difference is that there are many more statistically significant (at the 5 percent level) coefficients for the pseudo-panel.

Figure 5 provides visual confirmation that the pseudo-panel point estimates lie close to the local-projection point estimates.[11] The figure displays scatterplots of the pseudo-panel local-projection betas against the local-projection betas at horizons 0 and 7. In both cases, the data line up closely on the 45^o line. The point estimates diverge only in a couple of cases with very negative betas.

Figure 5: Country Temperature Pseudo-Panel Local-Projection Betas and Local-Projection Betas



Notes: The 45^o line is given in red. Local-projection betas are estimates from equation (6) and pseudo-panel local-projection betas are estimates from equation (7) for $h = 0$ and $h = 7$. For Horizon 7, two outliers not shown and are the Solomon Islands (49,35) and Equatorial Guinea (-84,-26).

We have heuristically argued that the pseudo-panel local-projection betas are largely undistorted from the local-projection betas but are significant for many more countries. But are the constrained pseudo-panel estimates econometrically justified? To answer this question, we conduct formal tests of the homogeneity restrictions within each pseudo panel. The complete set of results are relegated to Appendix D. Here, we note, of the 328 tests–one for each of the 41 pseudo panels across 8 horizons–only two rejects the homogeneity restriction at the 5 percent level. The data largely supports the limited pooling strategy and we proceed by reporting results from the pseudo panels.

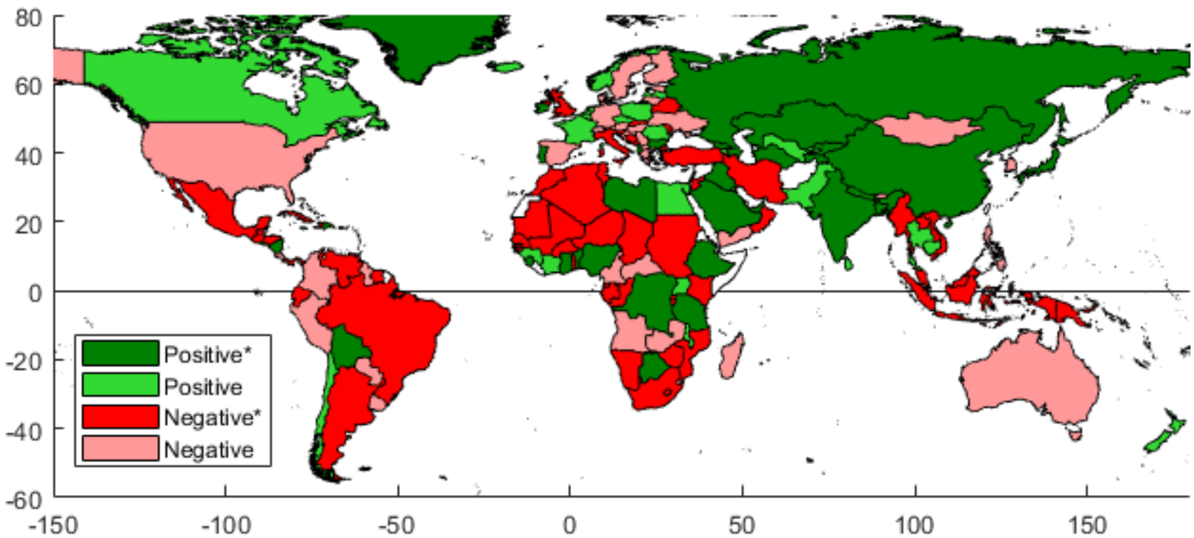
Figure 6 plots the pseudo-panel local-projection betas at horizons 0 and 7 onto a world map. Positive real GDP per capita growth responses are indicated in green and negative responses in red. Darker shades indicate statistical significance at the 5 percent level.

At horizon 0, negative growth responses tend to be geographically concentrated in developing economy regions of Latin America, Africa, and Southeastern Asia. Negative (but insignificant at

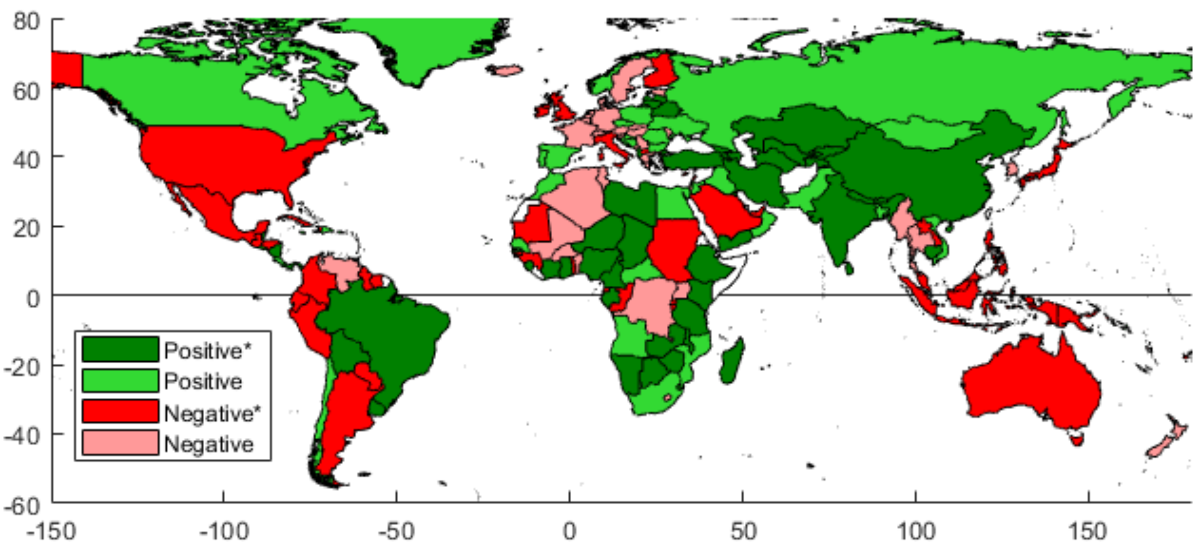
[11]The full set of pseudo-panel local projection impulse responses are also shown in Appendix C.

Figure 6: Pseudo-Panel Local Projection Impulse Responses to Country Temperature Shocks

Horizon 0



Horizon 7



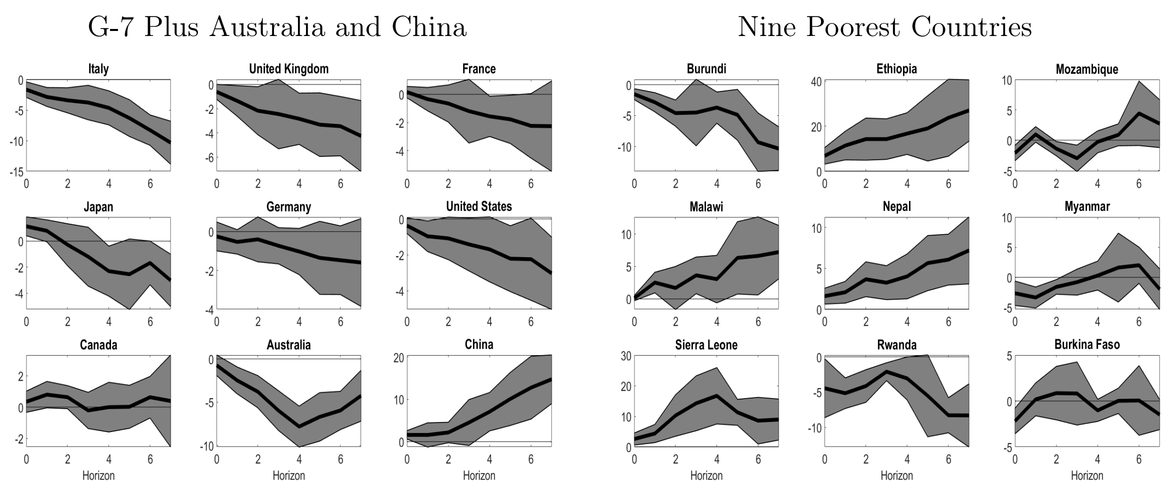
Notes: Country temperature pseudo-panel local-projection betas, $\beta_{j,h}$, are from equation (7) for $h = 0$ and $h = 7$. * indicates significance at the 5 percent level.

the 5 percent level) point estimates are obtained for the United States, Australia, Sweden, Finland, Germany, and Spain. Positive responses are obtained for high latitude countries such as Canada and Russia. Somewhat surprisingly, positive short-run growth responses are estimated for several African countries as well as India and China. Delving further into the mix between rich and poor countries, 60 percent of statistically significant negative responses were from poor countries.[12]

At horizon 7, statistically significant negative responses are estimated for several rich countries, such as the United States, United Kingdom, Italy, Japan, and Australia. On the other hand, the large developing economies of Brazil, Nigeria, India, and China have statistically significant positive responses. Negative responses outnumber positive responses for rich countries while two-thirds of statistically significant positive responses are for poor countries.

Figure 7 displays the pseudo-panel impulse responses for a set of rich and poor countries. The rich are represented by the G-7 countries plus Australia and China and the poor are the nine poorest countries in our sample, based on average real GDP per capita over the sample.[13] Amongst the rich, except for Canada and China, real GDP per capita declines following an increase in country temperature. Amongst the poorest countries, real GDP per capita increases following a positive country temperature shock in Ethiopia, Malawi, Nepal, and Sierra Leone.

Figure 7: Pseudo-Panel Impulse Responses of Growth to Country Temperature Shocks–Selected Rich and Poor Countries



Notes: Shaded areas are plus and minus 1.96 standard error bands.

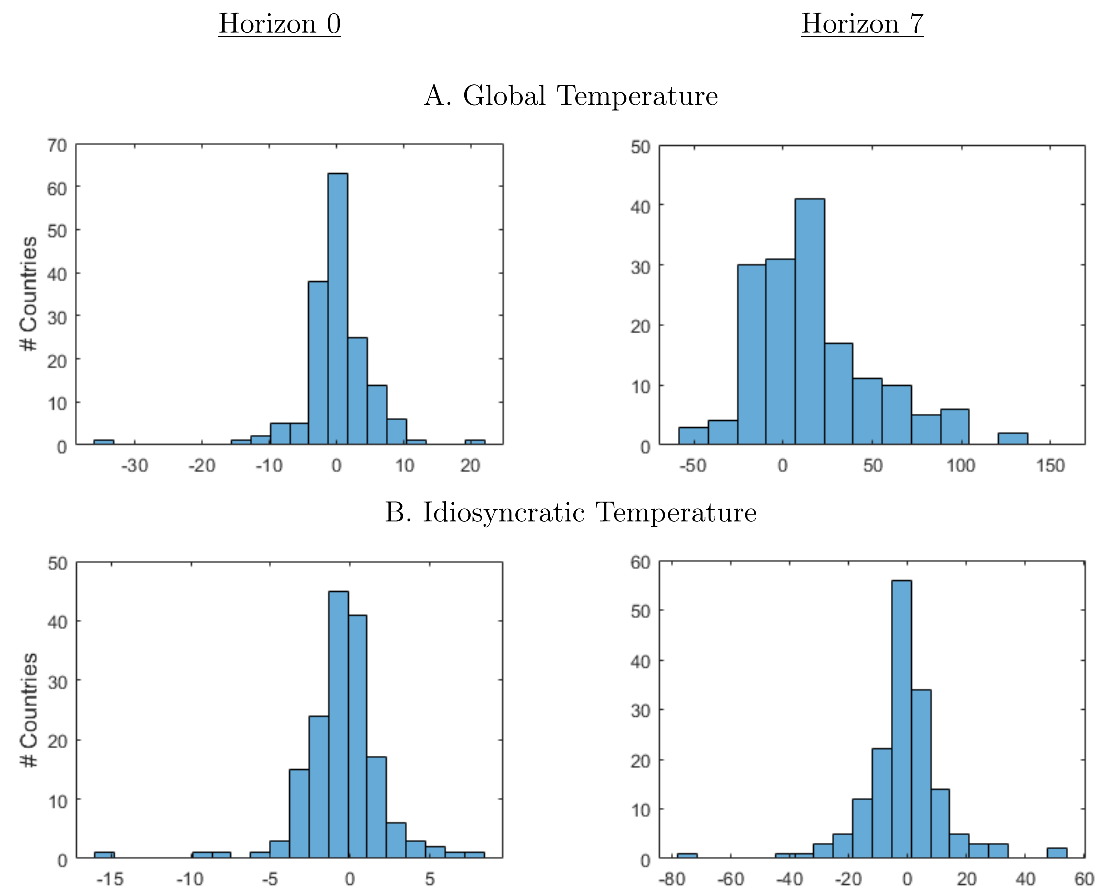
[12]Here, we followed Dell et al. (2012) and classify a country as poor (rich) if its real GDP per capita in the first year of the sample lies below (above) the global median.

[13]China is grouped with the rich countries, not on the basis of per capita GDP but because it is the world's second largest economy.

4.3 Local Projections with Global and Idiosyncratic Temperature

This section reports results for the responses of growth to global (τ_t) and idiosyncratic ($\tau^o_{j,t}$) temperature shocks. As with the country temperature results, we also report summaries of the results rather than showing all of the impulse response figures.[14] Figure 8 displays the histograms of the global (Panel A) and idiosyncratic (Panel B) temperature local-projection betas (in percent) at horizons 0 and 7. Again, extensive heterogeneity is observed in the responses. At horizon 0, both global and idiosyncratic local-projection beta distributions are slightly skewed left, as is the horizon 7 idiosyncratic beta distribution. In contrast, the distribution of horizon 7 global temperature local-projection betas is evidently skewed right.

Figure 8: Global and Idiosyncratic Temperature Local-Projection Betas



Notes: Distribution of global temperature (τ_t) and idiosyncratic temperature ($\tau^o_{j,t}$) local-projection betas, $\beta_{j,h}$, from equation (6) for $j = 1, ..., 162$ and $h = 0$ and 7.

Table 3 reports the summary comparison between the local-projection and pseudo-panel local-

[14] The full set of impulse responses to global and idiosyncratic temperature shocks are shown in Appendix E.

Table 3: Global and Idiosyncratic Temperature Local Projection and Pseudo Panel Local Projection Summary

A. Global Temperature

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	76	74	76	75	70	62	53	51	78	74	78	74	70	62	54	50
# pos	86	88	86	87	92	100	109	111	84	88	84	88	92	100	108	112
# sig neg	5	6	9	12	15	16	13	14	38	34	38	54	42	42	42	42
# sig pos	4	7	15	18	15	30	34	42	48	56	52	48	72	68	84	88

B. Idiosyncratic Temperature

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	97	88	86	98	100	93	92	93	98	90	86	98	102	94	90	94
# pos	65	74	76	64	62	69	70	69	64	72	76	64	60	68	72	68
# sig neg	10	13	16	17	18	16	16	18	62	66	58	58	58	62	62	66
# sig pos	8	2	4	8	6	8	9	9	36	36	40	36	36	32	32	36

Notes: This table shows the count of global (Panel A) and idiosyncratic (Panel B) temperature local-projection (estimates from equation (6)) and pseudo-panel local-projection (estimates from equation (7)) betas that are negative (neg), positive (pos), and statistically significant at the 5 percent level (sig neg and sig pos).

projection betas. Panel A shows results for global temperature shocks and Panel B, for idiosyncratic shocks.[15] As before, comparing across estimation methods and horizons again reveals nearly identical numbers of positive and negative point estimates but many more statistically significant pseudo-panel estimates. Looking at responses to global temperature shocks (Panel A), positive betas typically outnumber negative betas, whereas the opposite is the case for idiosyncratic temperature shocks (Panel B). The majority of growth responses to idiosyncratic temperature shocks are negative, which is qualitatively consistent with the panel regression studies. This makes sense because the idiosyncratic temperature component is similar to temperature variation employed in panel studies with common time fixed effects.

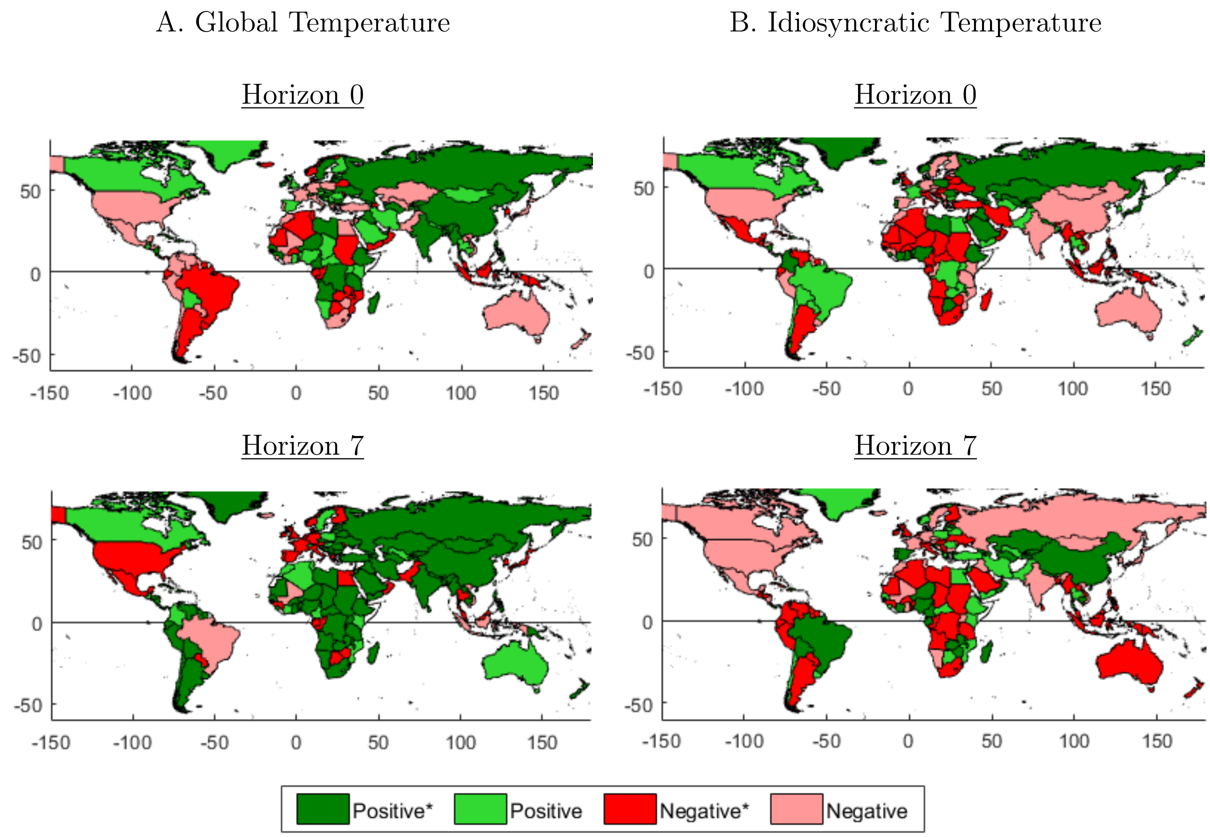
For the local-projection results, from horizons 2 through 7, the total number of significant negative and significant positive responses to global temperature shocks substantially dominates those for country and idiosyncratic temperature shocks. Similarly, the total number of significant negative and positive responses from the pseudo-panel estimates dominates from horizons 3 through 7.

Here, as well, limited pooling into pseudo panels can be econometrically justified. Appendix D reports the results of formal tests of the homogeneity restrictions within each pseudo panel. Here, we mention that none of the 328 tests with global temperature and none of the 328 tests with idiosyncratic temperature reject the restrictions at the 5 percent level.

Figure 9 plots the pseudo-panel local-projection betas at horizons 0 and 7 onto a world map.

[15] The complete set of impulse responses to global and idiosyncratic temperature shocks are shown in Appendix E.

Figure 9: Global and Idiosyncratic Temperature Pseudo-Panel Local-Projection Betas



Notes: Global (Panel A) and idiosyncratic (Panel B) temperature pseudo-panel betas, $\beta_{j,h}$, are from equation (7) for $h = 0$ and $h = 7$. * indicates significance at the 5 percent level.

Results for global temperature shocks are in Panel A and idiosyncratic temperature shocks in Panel B. As before, negative responses are shown in red and positive responses in green with darker shades indicating statistical significance at the 5 percent level.

At horizon 0, negative responses to global temperature shocks are found in both high (e.g., Denmark, South Korea, and Norway) and low (e.g., Algeria, Zambia, and Mozambique) income countries. Positive responses seem to be more prevalent in the higher latitude countries, but also by both rich and poor countries. At horizon 7, however, negative responses are more clearly seen primarily for rich countries. In fact, six of the Group of 7 (G-7) country responses are significantly negative (Canada being the exception). Surprisingly, a majority of the poorest countries experience significantly positive growth responses to positive global temperature shocks.

In response to idiosyncratic temperature shocks, negative responses outnumber positive ones. This is most apparent at horizon 7 where many of the rich countries have negative responses although most are statistically insignificant (the exceptions are the United Kingdom, Italy, and

Australia). While the large middle income countries of China and Brazil have positive responses, a large share of the significantly negative responses come from the poorer countries in South America, Africa, and Southeastern Asia.

The direction of the responses to global and idiosyncratic temperature shocks often go in opposite directions. If country temperature $\tau_{j,t}$ is ultimately the causal factor, global and idiosyncratic temperature components represent two separate pathways for temperature to affect growth.

Which of these factors dominate quantitatively? Table 4 shows the correlation amongst the alternative pseudo-panel temperature betas. As can be seen, the correlation between global and idiosyncratic temperature betas is low at horizon 7 and is lower than the correlation between global and country temperature betas for both horizons 0 and 7. However, the correlation between country and idiosyncratic temperature betas is higher than between country and global temperature betas. Thus, in a general sense, the idiosyncratic temperature component can be said to dominate. However, the low horizon 7 correlation between idiosyncratic and global temperature betas indicates that the two temperature components pull in the same direction for a sizable proportion of countries and also pull in opposite directions for a sizable proportion of countries.

Table 4: Correlations of Pseudo-Panel Local-Projection Coefficients at Horizons 0 and 7

		Global	Idiosyncratic
Horizon 0	Country	0.663	0.945
	Global		0.450
Horizon 7	Country	0.529	0.849
	Global		0.132

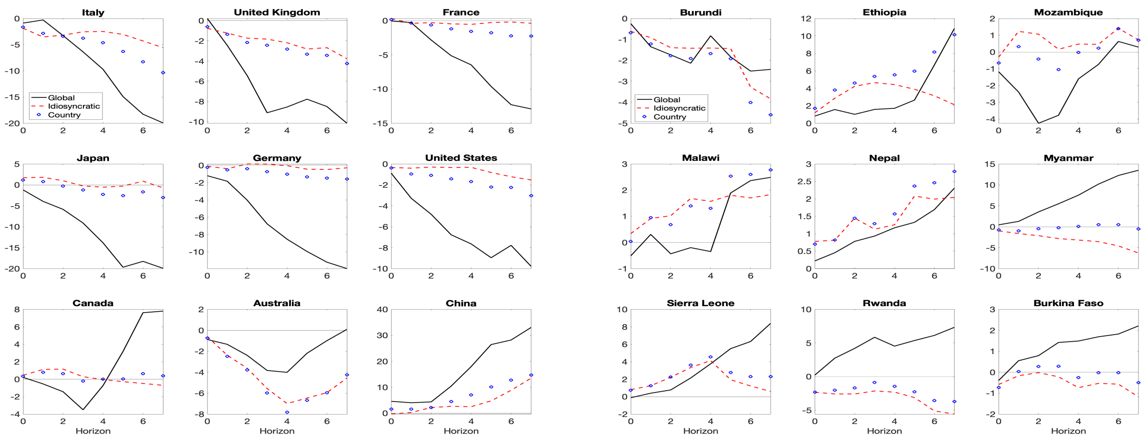
Figure 10 illustrates the variation in response to the alternative temperature shocks, again for the G-7 plus Canada and China and the poorest nine countries. For each country, the figure plots the impulse responses to the three shocks. In producing this figure, the shocks have been standardized to convey the growth response to a typically sized shock.

For the poorest countries, responses to country and idiosyncratic temperature shocks tend to move together. Their responses to country shocks seem to be governed mainly by the response to the idiosyncratic component. Responses to global and idiosyncratic temperature shocks strongly diverge for Myanmar, Rwanda, and Burkina Faso, and to a lesser extent for Mozambique and Sierra Leone. For the rich countries, responses to idiosyncratic and global temperature generally trend in the same direction. For Italy, the United Kingdom, and China, the directional correspondence is generally close. At horizons 5-7, the response of Canadian real GDP per capita growth to country temperature appears to be pulled by the global temperature component. From this limited analysis, the large developed economy responses to country temperature shocks might be said to be weakly dominated by the global temperature component.

Figure 10: Impulse Response Shock Comparison

G-7 Plus Australia and China

Nine Poorest Countries



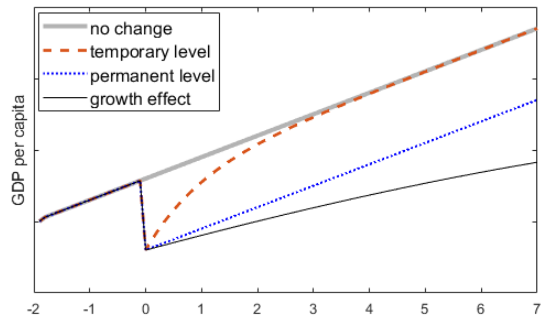
We summarize three main findings for the local projection and the pseudo-panel local projection results. First, there is substantial heterogeneity in responses to real GDP per capita growth from temperature variation, irrespective of the source. Second, there are more negative responses to idiosyncratic temperature increases – particularly in the developing world – which is qualitatively in line with previous findings. Third, in response to global temperature shocks, poor countries tend to exhibit positive growth responses while rich countries tend to exhibit negative responses, particularly at longer horizons.

4.4 Level versus Growth Effects

Do the temperature shocks result in long-lasting effects on growth, or only in the level of GDP? This section uses the estimated pseudo-panel local projections to distinguish between level effects and growth effects across countries over the eight horizons ($h \in \{0, ..., 7\}$) considered in this analysis.

Figure 11 presents a stylized representation of alternative effects on GDP. Suppose real GDP per capita evolves along a steady state growth path represented by the gray 'no change' line in the figure. At time 0, a (say positive) temperature shock is realized. The shock could cause a level (but not growth) response, which could be transitory (temporary) or permanent. In the transitory (temporary) level effect, shown by the dashed red line, output falls but recovers back to the original growth path. In the permanent level effect, shown by the blue hatched line, output falls then resumes growth but on a permanently lower level than the initial growth path. A negative growth effect is illustrated by the black line where the shock causes output to decline after which

Figure 11: Stylized Negative Responses to Temperature Shock at Time 0



growth resumes but at a slower than pre-shock rate.

Our econometric evaluation of whether temperature shocks result in level or growth effects is as follows: We say a country experiences a pure negative growth effect from a temperature shock if conditional on the point estimate of $\hat{\beta}_7 < 0$ being negative, the hypothesis $\beta_7 = \beta_0$ is rejected. We say a country experiences only a (permanent or transitory) negative level effect if $\hat{\beta}_0$ is significantly negative and does not experience a negative growth effect. Tests for positive growth and level effects are specified symmetrically in the obvious fashion.[16]

Table 5 shows the results for country temperature shocks. Note, it is possible for a country to have a negative level effect and positive growth but these overlaps are infrequent (e.g., Chad and Zimbabwe, for which β_0 is significantly less than 0 and β_7 is significantly larger than β_0).[17] Negative growth effects are widespread. Over half (94) the countries show significant growth effects–positive or negative. Many of the 42 countries that exhibit negative growth effects are relatively rich (e.g., Belgium, Ireland, Italy, Japan, Luxembourg, Netherlands, and the United States), while many of the 52 countries that exhibit positive growth effects are relatively poor (e.g., Chad, Ethiopia, and Zimbabwe).

Table 6 shows the analogous results for global temperature shocks (Panel A) and idiosyncratic temperature shocks (Panel B). The growth effects from global temperature changes are quite extensive, with 92 of 162 countries showing significant positive growth effects. 39 countries show negative growth effects, and many of them are relatively high income countries (Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Japan, Norway, Spain, and United Kingdom).

[16]Our analysis does not distinguish between permanent and temporary level effects, however. Since the analysis is restricted to only eight horizons ($h \in \{0, ..., 7\}$) we are somewhat constrained in capturing true (i.e., long-run) level and growth effects.

[17]Countries are classified into experiencing only a level effect as follows. Let A be the set of countries for which β_0 is significantly less than 0, B be the set of countries for which β_7 is significantly less than β_0, and C be the set for which β_7 is significantly greater than 0. Then the set of countries that experience only a negative level effect is $A - \{[A \cap B] \cup [A \cap C]\}$.

Table 5: Level and Growth Effects from Country Temperature Shock

Negative Level	Algeria	Bahamas, The	Belarus	Bosnia and Herzegovina
	Brazil	Burkina Faso	Cabo Verde	Chad
	Gabon	Iran, Islamic Rep.	Jordan	Kenya
	Lesotho	Mali	Moldova	Montenegro
	Morocco	Mozambique	Myanmar	Namibia
	Niger	Oman	Panama	Senegal
	Slovak Republic	Slovenia	South Africa	Tunisia
	Turkey	Vanuatu	Venezuela, RB	Vietnam
	West Bank and Gaza	Zimbabwe		
Negative Growth	Argentina	Belgium	Burundi	Colombia
	Comoros	Congo, Rep.	Cuba	Cyprus
	Ecuador	Equatorial Guinea	Fiji	Finland
	Guatemala	Guinea	Guinea-Bissau	Guyana
	Haiti	Honduras	Iceland	Indonesia
	Ireland	Italy	Japan	Lao PDR
	Lebanon	Luxembourg	Malaysia	Mauritania
	Mexico	Netherlands	North Macedonia	Papua New Guinea
	Paraguay	Philippines	Rwanda	Saudi Arabia
	Sudan	Suriname	Thailand	Trinidad and Tobago
	United Arab Emirates	United States		
Positive Level	Bangladesh	Benin	Bulgaria	Dominican Republic
	Greenland	Iraq	Ireland	Japan
	Lebanon	Portugal	Saudi Arabia	St. Vincent and the Grenadines
	United Arab Emirates			
Positive Growth	Albania	Armenia	Azerbaijan	Belarus
	Belize	Bhutan	Bolivia	Botswana
	Brazil	Brunei Darussalam	Cabo Verde	Cambodia
	Cameroon	Chad	China	Cote d'Ivoire
	Croatia	Eswatini	Ethiopia	Gabon
	Gambia, The	Georgia	Ghana	Iran, Islamic Rep.
	Jordan	Kazakhstan	Kenya	Kuwait
	Kyrgyz Republic	Latvia	Libya	Lithuania
	Madagascar	Namibia	Nicaragua	Niger
	Nigeria	Panama	Russian Federation	Samoa
	Sierra Leone	Solomon Islands	Sri Lanka	Tajikistan
	Tanzania	Turkey	Turkmenistan	Uruguay
	Uzbekistan	Yemen, Rep.	Zambia	Zimbabwe

In response to idiosyncratic temperature shocks, roughly the same number of countries exhibit negative growth (38) as do those exhibiting positive growth (36) effects from idiosyncratic temperature shocks. Amongst the rich countries whose growth responds negatively to idiosyncratic shocks are, Australia, Finland, Ireland, Italy, Luxembourg, and the Netherlands.

To summarize, temperature changes result in both short-term level effects and medium-term growth effects in national economies. All three temperature shocks induce these effects. Many rich countries experience negative growth effects. A majority of the countries in our sample have historically experienced positive growth effects from changes in global temperature.

Table 6: Level and Growth Effects from Global and Idiosyncratic Temperature Shocks

A. Global Temperature Shocks				
Negative Level	Algeria	Argentina	Azerbaijan	Belarus
	Brazil	Burkina Faso	Ecuador	Iceland
	Indonesia	Lebanon	Lesotho	Malawi
	Mauritania	Mozambique	Panama	Papua New Guinea
	Sudan	Suriname	Tunisia	Uruguay
	Yemen, Rep.	Zambia		
Negative Growth	Austria	Bahamas, The	Belgium	Belize
	Botswana	Burundi	Congo, Rep.	Cyprus
	Denmark	Egypt, Arab Rep.	Equatorial Guinea	Finland
	France	Gabon	Gambia, The	Germany
	Greece	Guinea-Bissau	Ireland	Italy
	Iraq	Japan	Korea, Rep.	Luxembourg
	Malaysia	Mexico	Moldova	Norway
	Oman	Pakistan	Paraguay	Portugal
	Puerto Rico	Spain	St. Vincent and the Grenadines	Thailand
	United Kingdom	West Bank and Gaza	Zimbabwe	
Positive Level	Cameroon	Cyprus	Eswatini	Fiji
	Guinea	Hungary	Ireland	Jamaica
	Slovenia	Sweden	Ukraine	United Arab Emirates
Positive Growth	Albania	Angola	Argentina	Armenia
	Azerbaijan	Bangladesh	Belarus	Benin
	Bhutan	Bolivia	Bosnia and Herzegovina	Brunei Darussalam
	Bulgaria	Burkina Faso	Cabo Verde	Cambodia
	Central African Republic	Chad	Chile	China
	Comoros	Congo, Dem. Rep.	Costa Rica	Croatia
	Cuba	Czech Republic	Dominican Republic	Ecuador
	El Salvador	Estonia	Ethiopia	Georgia
	Ghana	Greenland	Guyana	Honduras
	India	Iran, Islamic Rep.	Peru	Jordan
	Rwanda	Saudi Arabia	Kyrgyz Republic	Lao PDR
	Latvia	Libya	Sri Lanka	Madagascar
	Suriname	Switzerland	Mongolia	Togo
	Myanmar	Namibia	Nepal	New Zealand
	Nicaragua	Niger	Nigeria	North Macedonia
	Panama	Papua New Guinea	Peru	Philippines
	Poland	Romania	Russian Federation	Rwanda
	Samoa	Saudi Arabia	Senegal	Serbia
	Sierra Leone	Slovak Republic	Solomon Islands	South Africa
	Sri Lanka	Sudan	Suriname	Tajikistan
	Tanzania	Trinidad and Tobago	Tunisia	Turkey
	Turkmenistan	Uganda	Ukraine	Uruguay
	Vanuatu	Venezuela, RB	Yemen, Rep.	Zambia
B. Idiosyncratic Temperature Shocks				
Negative Level	Bahamas, The	Belarus	Bhutan	Bosnia and Herzegovina
	Cabo Verde	Cameroon	Central African Republic	Croatia
	Gabon	Iran, Islamic Rep.	Jordan	Lithuania
	Madagascar	Mali	Mexico	Namibia
	Niger	Oman	Senegal	Solomon Islands
	Turkey	Vietnam	Zimbabwe	
Negative Growth	Algeria	Angola	Argentina	Australia
	Benin	Brunei Darussalam	Burkina Faso	Burundi
	Chad	Colombia	Comoros	Congo, Dem. Rep.
	Congo, Rep.	Cuba	Cyprus	Ecuador
	Equatorial Guinea	Fiji	Finland	Guatemala
	Guinea-Bissau	Guyana	Haiti	Honduras
	Indonesia	Ireland	Italy	Lao PDR
	Lebanon	Libya	Luxembourg	Malaysia
	Mauritania	Myanmar	Netherlands	North Macedonia
	Papua New Guinea	Paraguay		
Positive Level	Botswana	Colombia	Greenland	Iceland
	Iraq	Ireland	Israel	Nicaragua
	Norway	Poland	Romania	Russian Federation
	Samoa	Saudi Arabia	Sierra Leone	St. Vincent and the Grenadines
	Uzbekistan			
Positive Growth	Albania	Armenia	Azerbaijan	Bahamas, The
	Belize	Bolivia	Brazil	Cabo Verde
	Cambodia	Cameroon	China	Cote d'Ivoire
	Dominican Republic	Eswatini	Ethiopia	Gabon
	Georgia	Iran, Islamic Rep.	Jamaica	Kazakhstan
	Kuwait	Kyrgyz Republic	Malawi	Niger
	Oman	Panama	Portugal	Puerto Rico
	Solomon Islands	Spain	Tajikistan	Turkmenistan
	West Bank and Gaza	Yemen, Rep.	Zambia	Zimbabwe

5 Robustness

We evaluated the sensitivity of our results by performing a number of robustness checks. First, we add lagged temperature in the local-projections regressions (as in Dell et al. (2012)). Table 7 shows the local-projection beta and pseudo-panel local-projection beta summary on current temperature when current and lagged temperature are both included in the regression. Comparison of Panel A with Table 2, and Panels B and C with Table 3 shows very little overall difference in the impulse response signs and significance from adding lagged temperature.

Table 7: Local Projection and Pseudo Panel Local Projection Summary – Adding Lagged Temperature

A. Country Temperature

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	96	93	91	89	85	79	78	73	94	86	90	86	82	82	78	78
# pos	66	69	71	73	77	83	84	89	68	76	72	76	80	80	84	84
# sig neg	8	11	13	14	14	13	9	8	55	54	54	46	58	46	47	46
# sig pos	7	4	6	9	6	5	9	10	28	40	44	32	36	44	44	48

B. Global Temperature

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	88	72	78	81	67	64	57	52	86	74	70	78	70	62	54	54
# pos	74	90	84	81	95	98	105	110	76	88	92	84	92	100	108	108
# sig neg	6	4	6	7	12	13	10	14	43	26	26	30	34	42	42	42
# sig pos	7	4	9	9	11	26	32	39	40	40	44	40	64	68	80	76

C. Idiosyncratic Temperature

	Local-Projection Beta								Pseudo-Panel Local-Projection Beta							
Horizon	0	1	2	3	4	5	6	7	0	1	2	3	4	5	6	7
# neg	97	97	83	98	99	96	90	92	94	86	82	102	98	98	86	94
# pos	65	65	79	64	63	66	72	70	68	76	80	60	64	64	76	68
# sig neg	9	10	15	15	20	16	15	14	62	58	58	58	58	58	66	66
# sig pos	6	6	6	7	7	6	6	8	32	28	28	28	32	36	32	28

Notes: This table shows the count of country (Panel A), global (Panel B), and idiosyncratic (Panel C) temperature local-projection (estimates from equation (6) with lagged temperature in the regression) and pseudo-panel local-projection (estimates from equation (7) with lagged temperature in the regression) betas that are negative (neg), positive (pos), and statistically significant at the 5 percent level (sig neg and sig pos).

Additionally, we evaluated the sensitivity of our results to the following variations: We used the first principal component of quadratically detrended temperature as global temperature. We linearly detrended temperature. We cubically detrended temperature. We used 1990 population weighted temperature. We detrending temperature by first differencing.

Results for these robustness checks are reported in Appendix F. Only when detrending by first differencing temperature do the results change, by reducing the persistence of the impulse response. There continue to be significant positive and negative growth responses at horizons 0 through 4. This result is not unexpected, however. The reduction in persistence is typical in vector autoregressions where stationarity is induced by first differencing instead of regressing on time.

6 Cross-Sectional Response Heterogeneity and Country Characteristics

What explains the response heterogeneity across countries? This section investigates how response variation may be systematically related to country characteristics. We consider the role of a country's geography, economic structure, level of growth, and development on whether weather positively or negatively impacts its growth. The analysis is based on a cross-sectional regression of the local-projection betas on country characteristics.[18] Although the betas are estimated, there is no 'second stage' or generated regressors problem because the estimated response coefficients are the dependent variable in the regressions.

We include the country's (absolute value of) latitude primarily as a control variable. Country latitude is negatively correlated with its average temperature, and the inverse relationship between temperature and growth in the cross-section is well known (Dell et al., 2009). We are primarily interested in the explanatory power of various economic characteristics after controlling for latitude.

In light of panel studies finding response differences for rich and poor countries, we include average real GDP per capita in logarithmic form. Extant research would lead one to expect log income to enter with a positive coefficient. We also consider a country's long-horizon growth rate. This is the growth rate of real GDP per capita from beginning to the end of the sample.

We also examine features of each country's economic structure. Here, we include the average GDP share of agriculture, industry, and manufacturing, all in logarithmic form. Agriculture has long been seen as a very direct channel through which temperature affects the economy. Agricultural workers, especially in poorer countries, are directly exposed to temperature as are the crops themselves, and Deryugina and Hsiang (2014), Deschênes and Greenstone (2007), Nelson et al. (2014), and Dietz and Lanz (2019) report empirical damage estimates to agriculture from high temperatures. In industrial or manufacturing settings, Hsiang et al. (2017b), Zander et al. (2015), Jessoe et al. (2018), Cai et al. (2018a), Zivin and Neidell (2014), Cachon et al. (2012), and Nath (2020) find that temperature lowers productivity, either through lower labor productivity or reduced labor supply. The effect is not only physical, but also mental. Park et al. (2020) and

[18] Recently, Lustig and Richmond (2020) employed the same methodology to regress exchange rate betas on gravity variables.

Cook and Heyes (2020) report how temperature extremes lower cognitive abilities. The economic variables are from the World Bank's, *World Development Indicators*.

Table 8 shows the correlation structure of the explanatory variables. Income is highly correlated with latitude, uncorrelated with long-horizon growth, and negatively correlated with agricultural share. Income is only slightly correlated with industrial share and manufacturing share.

Table 8: Correlations of Explanatory Variables

	GDPPC	Growth	Agriculture	Industy	Manufacturing
Latitude	0.516	0.106	-0.509	-0.052	0.138
GDPPC		-0.001	-0.609	0.143	0.055
Growth			-0.120	0.104	0.282
Agriculture				-0.406	-0.257
Industy					0.296

Notes: GDPPC is the logarithm of average real GDP per capita, Growth is measured from beginning to end of the available sample, and Agriculture, Industry, and Manufacturing are logarithms of the average sectoral shares of GDP.

Let X_j be the vector of country $j's$ characteristics and the regression constant. We run the cross-sectional regression,

$$\hat{\beta}_{j,h} = X_j'\gamma + u_h, \tag{8}$$

for country, global, and idiosyncratic temperature local-projection betas, $\hat{\beta}_{j,h}$, at $h = 0$ and $h = 7$.

Results for the country temperature local-projection betas are shown in Table 9. At horizons 0 and 7, the country temperature local-projection betas are, as expected, significantly increasing in latitude, which is consistent with the cross-sectional evidence in Dell et al. (2009). Unconditionally, growth responses to temperature shocks tend to be lower for warmer countries. When adding average real GDP per capita, however, this variable enters with a negative coefficient indicating that poor countries are more likely to experience higher growth responses to country temperature than rich countries. This conforms to the country-temperature world map (Figure 6) which showed growth for most of the rich, northern countries responded negatively overall to country temperature increases. Looking at the coefficient on growth, faster growing countries are more likely to be negatively impacted by increasing country temperature.

After controlling for latitude, average real GDP per capita, and long-term growth, a country's average agricultural share of GDP is not significant. It does consistently enter with a positive sign, however, which is interesting in the sense of suggesting that countries where agriculture plays a larger economic role are more likely to have benefited from rising temperature. This seems to go against the conventional wisdom whereby agricultural labor should be the most directly exposed to hot temperatures and where crop yields should be damaged by heat. It is, however, consistent with the inverse relation between response and income, since poor countries have larger

Table 9: Cross-Sectional Regression with Country Temperature Local-Projection Betas

Nobs	R^2	Latitude	GDPPC	Growth	Agriculture	Industry	Manufacturing
				Horizon 0			
162	0.048	**0.031**					
		(2.854)					
162	0.065	**0.045**	-0.283*				
		(3.318)	(-1.700)*				
162	0.102	**0.046**	-0.240	**-0.635**			
		(3.465)	(-1.457)	**(-2.525)**			
162	0.107	**0.045**	0.031	**-0.667**	0.375		
		(3.366)	(0.093)	**(-2.628)**	(0.953)		
161	0.105	**0.048**	-0.292	**-0.658**		0.418	
		(3.540)	(-1.633)	**(-2.573)**		(0.768)	
158	0.116	**0.046**	-0.206	**-0.566**			-0.660
		(3.456)	(-1.225)	**(-2.145)**			(-1.580)
158	0.132	**0.049**	0.052	**-0.619**	0.472	0.761	**-0.870**
		(3.566)	(0.156)	**(-2.330)**	(1.178)	(1.289)	**(-1.966)**
				Horizon 7			
162	0.009	0.068					
		(1.196)					
162	0.083	**0.215**	**-3.040**				
		(3.139)	**(-3.593)**				
162	0.135	**0.222**	**-2.776**	**-3.882**			
		(3.331)	**(-3.349)**	**(-3.062)**			
162	0.148	**0.213**	-0.520	**-4.147**	3.134		
		(3.195)	(-0.316)	**(-3.259)**	(1.588)		
161	0.156	**0.260**	**-3.308**	**-3.788**		4.342*	
		(4.001)	**(-3.885)**	**(-3.112)**		(1.676)*	
158	0.141	**0.233**	**-2.734**	**-3.566**			-0.541
		(3.608)	**(-3.384)**	**(-2.804)**			(-0.269)
158	0.169	**0.255**	-1.205	**-3.899**	2.897	5.154*	-1.946
		(3.847)	(-0.752)	**(-3.068)**	(1.511)	(1.825)*	(-0.920)

Notes: This table shows the results from equation (8) with the country temperature local-projection betas. Nobs is the number of observations, GDPPC is the logarithm of average real GDP per capita, Growth is measured from beginning to end of the available sample, and Agriculture, Industry, and Manufacturing are logarithms of the average sectoral shares of GDP. Heteroskedastic robust (White) t-ratios in parentheses. Bold indicates significance at the 5 percent level and '*' indicates significance at the 10 percent level.

agricultural sectors.

At horizon 7, the average industry's share of GDP is positive and significant at the 10 percent level. The average manufacturing's share of GDP enters negatively, but is not significant. Qualitatively, the negative coefficient on the average manufacturing share of GDP is consistent with Cachon et al. (2012) who finds excessive heat to lower productivity in United States auto manufacturing, Cai et al. (2018b) who find extreme temperatures in China decrease manufacturing labor productivity, and Somanathan et al. (2021) who find higher temperatures decrease labor productivity in Indian manufacturing. The positive sign on the average industry's share of GDP coefficient is unexpected. Industry, of which manufacturing is a subset, also includes value added in mining, construction, electricity, water, and gas. One possibility is that warmer weather extends the number of operational days in construction and mining. A thorough analysis of this conjecture is beyond the scope of this paper and is left for future work.

Table 10 shows the results from running analogous regressions for the global temperature local-projection betas. Qualitatively, the results are very similar to those for the country temperature local-projection betas. However, estimation seems to be more precise. At horizon 0, the coefficients on average real GDP per capita are now significant and both the average industrial share of GDP and average manufacturing share of GDP are significant at horizon 7. The coefficient on the average agriculture's share of GDP remains positive and insignificant.

Table 11 reports estimation results for the idiosyncratic temperature local-projection betas. Coefficient signs are generally consistent with those for country and global temperature local-projection betas, but are overall, less precisely estimated.

To summarize, we find a high degree of consistency in the point estimates across the responses to alternative temperature shocks. Latitude, average real GDP per capita, and long-term growth are the most robust variables. Average GDP shares of manufacturing and industry are significant in explaining responses to global temperature shocks, but not for country temperatures or their idiosyncratic components. The growth response to global temperature shocks is more systematically related to country economic structure characteristics, lending to an interpretation that global temperature represents the systematic component of country temperature.

We note that our results appear also to be consistent with long-difference regressions in Dell et al. (2012) who find that countries that warmed faster experienced slower growth. The connection between the two sets of results are that higher latitude countries are warming faster and they tend to be richer.

Table 10: Cross-Sectional Regression with Global Temperature Local-Projection Betas

Nobs	R^2	Latitude	GDPPC	Growth	Agriculture	Industry	Manufacturing
				Horizon 0			
162	0.034	**0.053**					
		(2.366)					
162	0.069	**0.093**	**-0.835**				
		(3.395)	**(-2.458)**				
162	0.135	**0.097**	**-0.716**	**-1.749**			
		(3.635)	**(-2.168)**	**(-3.463)**			
162	0.146	**0.093**	0.088	**-1.844**	1.117		
		(3.508)	(0.134)	**(-3.630)**	(1.417)		
161	0.135	**0.100**	**-0.755**	**-1.732**		0.316	
		(3.647)	**(-2.103)**	**(-3.376)**		(0.289)	
158	0.135	**0.098**	-0.658*	**-1.579**			-0.837
		(3.639)	(-1.946)*	**(-2.967)**			(-0.993)
158	0.149	**0.100**	0.075	**-1.694**	1.154	0.927	-1.120
		(3.584)	(0.110)	**(-3.155)**	(1.426)	(0.777)	(-1.254)
				Horizon 7			
162	0.010	0.217					
		(1.294)					
162	0.090	**0.665**	**-9.282**				
		(3.310)	**(-3.737)**				
162	0.208	**0.698**	**-8.105**	**-17.343**			
		(3.714)	**(-3.469)**	**(-4.854)**			
162	0.209	**0.693**	-6.826	**-17.494**	1.776		
		(3.661)	(-1.462)	**(-4.840)**	(0.317)		
161	0.324	**0.895**	**-12.759**	**-19.826**		**36.880**	
		(4.992)	**(-5.422)**	**(-5.892)**		**(5.149)**	
158	0.214	**0.689**	**-8.009**	**-17.418**			-3.864
		(3.611)	**(-3.351)**	**(-4.631)**			(-0.649)
158	0.352	**0.937**	**-9.113**	**-18.578**	5.089	**43.689**	**-14.833**
		(5.180)	**(-2.083)**	**(-5.354)**	(0.972)	**(5.666)**	**(-2.569)**

Notes: This table shows the results from equation (8) with the global temperature local-projection betas. Nobs is the number of observations, GDPPC is the logarithm of average real GDP per capita, Growth is measured from beginning to end of the available sample, and Agriculture, Industry, and Manufacturing are logarithms of the average sectoral shares of GDP. Heteroskedastic robust (White) t-ratios in parentheses. Bold indicates significance at the 5 percent level and '*' indicates significance at the 10 percent level.

Table 11: Cross-Sectional Regression with Idiosyncratic Temperature Local-Projection Betas

Nobs	R^2	Latitude	GDPPC	Growth	Agriculture	Industry	Manufacturing
				Horizon 0			
162	0.047	**0.031**					
		(2.798)					
162	0.056	**0.041**	-0.209				
		(2.985)	(-1.234)				
162	0.085	**0.042**	-0.170	**-0.577**			
		(3.103)	(-1.011)	**(-2.241)**			
162	0.091	**0.041**	0.134	**-0.612**	0.422		
		(3.000)	(0.400)	**(-2.360)**	(1.049)		
161	0.086	**0.043**	-0.201	**-0.604**		0.238	
		(3.072)	(-1.096)	**(-2.308)**		(0.427)	
158	0.097	**0.042**	-0.151	**-0.561**			-0.556
		(3.068)	(-0.881)	**(-2.077)**			(-1.302)
158	0.109	**0.043**	0.181	**-0.614**	0.530	0.469	-0.697
		(3.041)	(0.527)	**(-2.253)**	(1.291)	(0.774)	(-1.537)
				Horizon 7			
162	0.025	**0.127**					
		(2.038)					
162	0.052	**0.225**	**-2.026**				
		(2.921)	**(-2.124)**				
162	0.060	**0.228**	**-1.909**	-1.719			
		(2.966)	**(-1.994)**	(-1.174)			
162	0.080	**0.216**	1.063	-2.068	4.127*		
		(2.816)	(0.561)	(-1.411)	(1.814)*		
161	0.071	**0.242**	-1.809*	-1.225		-0.642	
		(3.211)	(-1.832)*	(-0.868)		(-0.214)	
158	0.071	**0.243**	**-1.926**	-1.425			0.739
		(3.271)	**(-2.070)**	(-0.973)			(0.319)
158	0.085	**0.228**	0.527	-1.691	3.266	-0.838	0.787
		(2.959)	(0.283)	(-1.144)	(1.466)	(-0.255)	(0.320)

Notes: This table shows the results from equation (8) with the idiosyncratic temperature local-projection betas. Nobs is the number of observations, GDPPC is the logarithm of average real GDP per capita, Growth is measured from beginning to end of the available sample, and Agriculture, Industry, and Manufacturing are logarithms of the average sectoral shares of GDP. Heteroskedastic robust (White) t-ratios in parentheses. Bold indicates significance at the 5 percent level and '*' indicates significance at the 10 percent level.

7 Assessing Economic Effects of Future Temperature Change: 2017-2100

As in Kahn et al. (2019), Colacito et al. (2019), and Hsiang et al. (2017b), we combine future temperature scenarios with our historical estimates of the effect of temperature shocks on real GDP per capita growth to perform counterfactual analysis from 2017 to 2100, and to construct empirical damage functions. The disaggregated nature of our estimates provides information about the geographical incidence of the economic consequences of projected future global warming and can be informative in IAM damage function specifications. We do caution, however, that these projections, which are based on historical relationships, may not be a reliable guide to future relationships, either due to a new relationship taking hold at high and previously unexperienced temperatures, environmental tipping points, shifting population, or from adaption to higher temperatures by economic agents.

7.1 Projected Temperature Changes

Our future temperature projections come from the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (Eyring et al., 2016).[19] Using monthly temperature and global coordinates for 25 CMIP6 models, we calculate average annual temperature by country from 2017-2100 under two future climate scenarios.[20] The first is SSP1-2.6. It is based on low emissions pathway, low mitigation challenges, and the Representative Concentration Pathway (RCP) 2.6. This scenario represents the lower end (most optimistic) of global climate change possibilities. The second scenario is SSP5-8.5 which is based on high climate change, high mitigation challenges, and RCP-8.5. This 'business-as-usual' case represents a high emissions pathway and the high end of climate change possibilities.

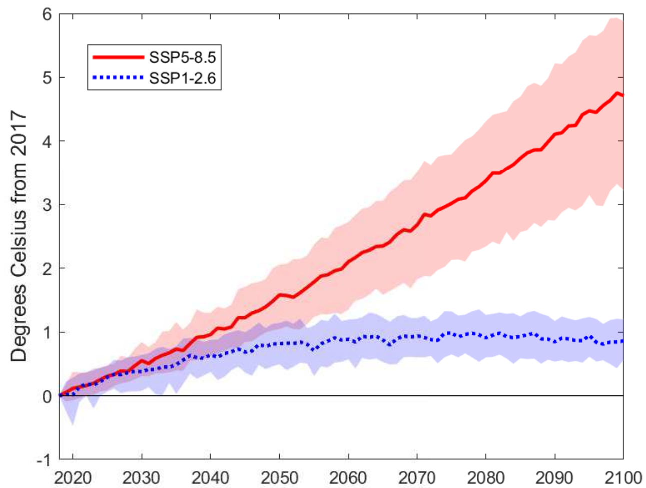
Figure 12 plots the average annual temperature for the SSP1-2.6 and SSP5-8.5 pathways across the countries in our sample.[21] The shaded areas are bound from above and below by the 90^{th} and 10^{th} percentile of model temperature projections. While there is a range of projected temperature changes across the models and scenarios, the average temperature increases by 2100 are close to 1 degree Celsius for the SSP1-2.6 scenario and nearly 5 degrees Celsius for SSP5-8.5.

[19]We acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modelling, coordinated and promoted CMIP6. We thank the climate modeling groups for producing and making available their model output, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF.

[20]The model list is in Appendix G.

[21]This only includes surface temperatures and is taken as an average across countries irrespective of geographic size.

Figure 12: SSP1-2.6 and SSP5-8.5 Future Temperature Scenarios



Notes: The SSP1-2.6 and SSP5-8.5 are the mean annual temperatures across the sample of countries from the 25 CMIP6 models relative to 2017. The shaded areas are the middle 80 percent of model projections for each climate scenario.

7.2 Modeling Economic Effects of Future Temperature Change

The counterfactual analysis is conducted only with country-level projected temperature changes. To perform this analysis, we need to make an adjustment with regard to how the temperature projections are inputted. In estimation, we detrended temperature to induce stationarity. However, using detrended temperature projections in the counterfactual analysis would be silly because warming would be removed by detrending. Since the country temperature local projection slopes measure the growth response to country temperature shocks $\partial \Delta y_{j,t}/\partial \tau_{j,t}$, we feed projected temperature changes $\Delta T_{j,t}$ into our estimated equations. With global warming taking place, there will be more positive temperature changes than negative ones. The economic effects of rising temperatures will then be observed by cumulating these changes.

Since we have, for each country, estimated local projections at horizons 0 through 7, we want to exploit all 8 estimates in obtaining a joint prediction for future output. To do this, note that at horizon h, backshifting equation (6) by horizon and conditioning on lagged temperature and lagged growth rates, gives 8 separate (although correlated) implied values of $y_{j,t}$. Then taking the appropriate differences we obtain 8 separate implied one-period growth rates. The average of these 8 values is taken as the implied growth rate. We compute these implied growth rates from 2017 to 2100 under a global warming scenario and under a 'no temperature change' scenario. Cumulating these growth rates gives, at year 2100, the damage (or benefit) implied by rising temperature.[22]

7.3 Projections of Future Economic Impact from Temperature Change

Figure 13 shows net economic damages (in percent) induced by temperature change from 2017 to 2100 under the lower emissions SSP1-2.6 temperature scenario. Benefits are shown in green and damages in red. Economic gains from temperature change are projected for China, Central and Southern Asia, Southern Africa, and Eastern Europe. Damages are projected for Southeastern Asia and the countries in Oceania. The loss to the United States is projected to be 0.5 percent. Gains to the large middle-income countries are projected to be 2.4 percent for China, 1.6 percent for India, and 1.1 percent for Brazil.

Figure 14 shows net projected damages under the high emissions scenario (SSP5-8.5). Obviously, the geographical patterns of economic gains and losses are similar to the lower emissions scenario (SSP1-2.6) but the magnitudes are amplified due to the higher temperature time-path. Here, the projections for the United States are a loss of 1.9 percent in 2100. In a granular geographical IAM model, Alvarez and Rossi-Hansberg (2021) estimate future productivity gains in the most northern latitudes due to rising temperatures – something we also find for countries such as Russia and Canada. However, they estimate the largest losses to occur in tropical regions whereas our results find gains and losses in the tropics to be country and region specific. We estimate losses for Southeastern Asia, gains for South Asia, and varied outcomes for tropical countries in Latin America and Africa.

Gains are projected for the large middle income countries of China, India, and Brazil, but the pattern is not clear for the lowest income countries. The large African countries of Ethiopia and Nigeria show output gains while others such as Uganda and D.R. Congo show projections of small losses.

[22] For country j, shifting the fitted part of the horizon h local projection equation backwards h periods gives, $y_{j,t} - y_{j,t-h-1} = c_{j,h} + \beta_{j,h}\Delta T_{j,t-h} + \sum_{k=1}^{2} \delta_{j,h,k}\Delta y_{j,t-h-1-k}$. Similarly, shifting backwards the horizon $h-1$ equation h periods gives, $y_{j,t-1} - y_{j,t-h-1} = c_{j,h-1} + \beta_{j,h-1}\Delta T_{j,t-h} + \sum_{k=1}^{2} \delta_{j,h-1,k}\Delta y_{j,t-h-1-k}$. Subtracting the second equation from the first gives an implied one-period growth rate from horizon h and $h-1$ local projections, $\Delta y_{j,t}(h) = (c_{j,h} - c_{j,h-1}) + (\beta_{j,h} - \beta_{j,h-1})\,\Delta T_{t_{j,t-h}} + \sum_{k=1}^{2} (\delta_{j,h,k} - \delta_{j,h-1,k})\,\Delta y_{j,t-h-1,k}$. Using our estimates for $h = 0, ...7$, we have 7 implied annual growth rates at time t, but we also have a direct implied growth rate from the $h = 0$ regression. Taken together, we have 8 projected time t annual growth rates conditioned on projected temperatures prior to t. The implied growth rate is the average implied growth rate across the 8 horizons h,

$$\frac{1}{8}\sum_{h=0}^{7}\Delta y_{j,t}(h) = \frac{1}{8}\left(c_{j,7} + \beta_{j,7}\Delta T_{j,t-7} + \sum_{h=0}^{6}\beta_{j,h}\left(\Delta T_{j,t-h} - \Delta T_{j,t-h-1}\right) + \sum_{k=1}^{9}\Psi_{j,k}\Delta y_{j,t-k}\right),$$

where

$$\Psi_{j,1} = \delta_{j,0,1},\ \ \Psi_{j,2} = (\delta_{j,0,2} + \delta_{j,1,1} - \delta_{j,0,1}),\ \ \Psi_{j,3} = (\delta_{j,1,2} - \delta_{j,0,2} + \delta_{j,2,1} - \delta_{j,1,1}),$$
$$\Psi_{j,4} = (\delta_{j,2,2} - \delta_{j,1,2} + \delta_{j,3,1} - \delta_{j,2,1}),\ \ \Psi_{j,5} = (\delta_{j,3,2} - \delta_{j,2,2} + \delta_{j,4,1} - \delta_{j,3,1}),$$
$$\Psi_{j,6} = (\delta_{j,4,2} - \delta_{j,3,2} + \delta_{j,5,1} - \delta_{j,4,1}),\ \ \Psi_{j,7} = (\delta_{j,5,2} - \delta_{j,4,2} + \delta_{j,6,1} - \delta_{j,5,1}),$$
$$\Psi_{j,8} = (\delta_{j,6,2} - \delta_{j,5,2} + \delta_{j,7,1} - \delta_{j,6,1}),\ \text{ and }\ \Psi_{j,9} = (\delta_{j,7,2} - \delta_{j,6,2}).$$

Figure 13: Percent Change in Real GDP Per Capita Between 2017 and 2100: SSP1-2.6 Scenario Relative to No Temperature Change Scenario

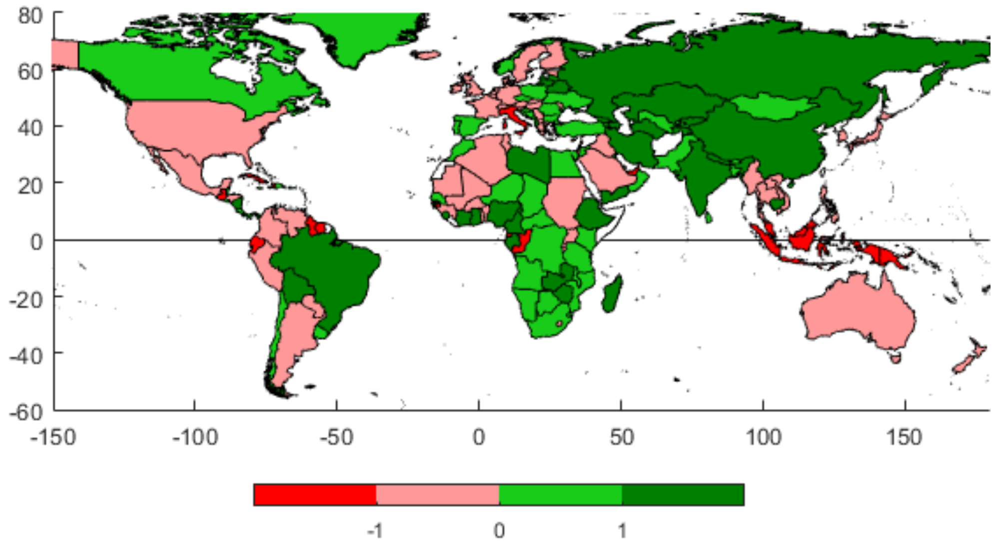
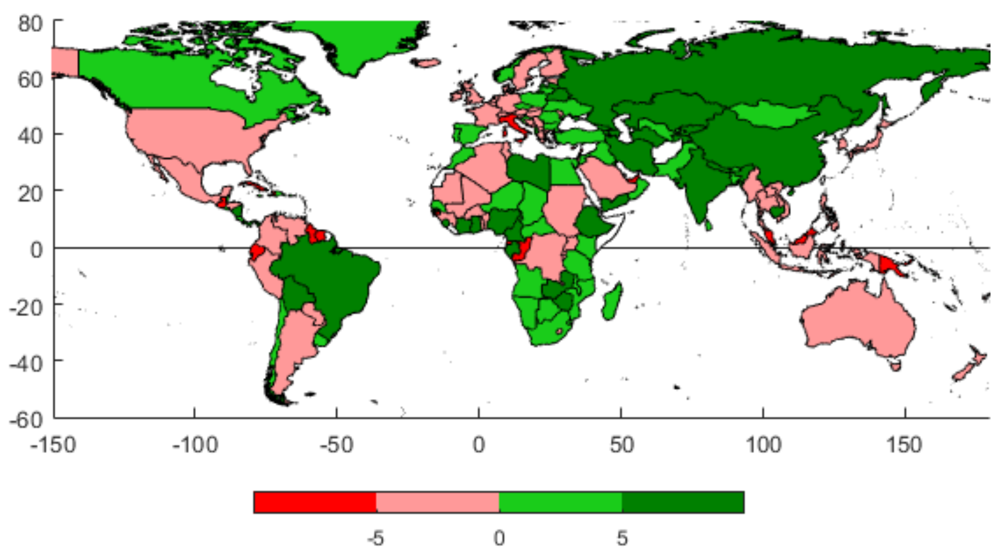
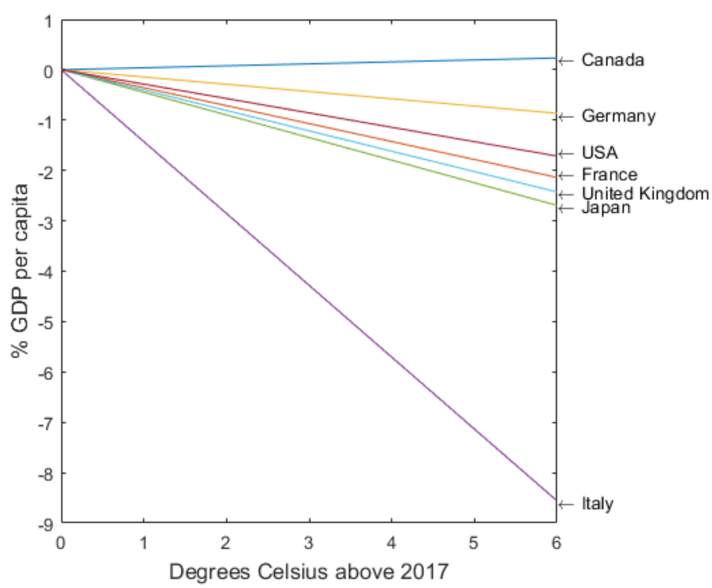


Figure 14: Percent Change in Real GDP Per Capita Between 2017 and 2100: SSP5-8.5 Scenario Relative to No Temperature Change Scenario



Henseler and Schumacher (2019) finds the negative relationship between GDP per capita growth and temperature increases to be primarily driven by poor countries. Projections in regional IAM models Nordhaus and Yang (1996) and the Anthoff-Tol FUND model used in Tol (2020) also predict that greater economic damage for hot, poor, and lower latitude countries than cool, rich, and high latitude countries.[23] These predictions generally conform to the concerns specified in the Stern report (Stern, 2007), which argued high latitude countries such as Canada and Russia stand to benefit from warming, while poor countries are most vulnerable due to higher geographic exposure, fewer resources available for mitigation, and poor quality housing. Also, Alvarez and Rossi-Hansberg (2021) estimate the greatest welfare losses (up to 15%) will occur in hot regions such as Africa, India, and Australia but also significant welfare gains (up to 14%) in the cold regions of Alaska, Northern Canada, and Siberia. In contrast, we project losses for rich countries. Except for Canada, losses are projected for the G-7 under both the low and high emissions scenarios.

Figure 15: G-7 Percent Change in Real GDP Per Capita in 2100 with Increase in Country Temperature



Notes: The time path of country temperature from the SSP5-8.5 projections are scaled so that the 2100 temperature is the degrees Celsius above 2017 indicated in the x-axis.

As a further illustration of G-7 vulnerability to rising future temperature, Figure 15 plots empirical damage functions for each of the G-7 countries. The figure shows gains or losses for

[23] See also Golosov et al. (2014) and Cai and Lontzek (2019) for more recent single-decision maker IAMs.

real GDP per capita in 2100 for increased temperature between 0 and 6 degrees Celsius from 2017. Canada will be largely unaffected, but each of the remaining countries in the G-7 will suffer increasing losses with higher temperature.

8 Conclusion

This paper reexamines the relationship between rising temperature and real GDP per capita growth, but from a country-specific time series perspective using local projections (Jordà, 2005). Three measures of temperature are analyzed: country temperature, global temperature, and idiosyncratic temperature, where the later two are decompositions of the former. We find substantial heterogeneity across countries, more than was previously reported in the literature, in the impulse responses of real GDP per capita growth to shocks to our three measures of temperature. Qualitatively consistent with the previous literature though, there are more negative than positive impulse responses of real GDP per capita growth to increases in idiosyncratic temperature. On the other hand, there are more positive than negative responses to increases in global temperature, whereas the responses vary by horizon for increases in country temperature. Richer countries, in particular, such as the United States, tend to experience negative impulse responses of real GDP per capita growth to increases in temperature, regardless of the temperature source.

The determinants of cross-country response variation in cross-sectional regressions of local projection (country, global, and idiosyncratic) temperature impulse response coefficients on country characteristics are also investigated. After controlling for latitude, the real GDP per capita growth impulse response coefficients are decreasing in average real GDP per capita and decreasing in long-horizon growth. The cross-sectional results suggest that global temperature may have a more systematic effect on growth than either country or idiosyncratic temperature variations. We can only speculate at this point that the elevated dependence of economic activity on global rather than country temperature may work through indirect effects of a world economy connnected through trade and finance.

Counterfactual analyses and empirical damage functions are constructed to assess the economic damage or benefit resulting from rising temperature as well. Our estimates, which are based on the historical relationship between real GDP per capita growth and temperature, and may not be stable in the future, suggest that future rising temperature is associated with economic losses for many rich countries, such as the United States, and economic benefits for large developing countries, such as India.

These results may be helpful in framing climate change policy. Stern (2008) argues, as a matter of ethics, rich countries should pay more for greenhouse gas abatement than developing countries, since the industrialized world is responsible for emitting most of the current stock of greenhouse gasses. In addition to ethical considerations, our findings that temperature increases have resulted in significant economic damages to rich countries suggests that they should also invest in abatement policies out of self-interest.

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