Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis*

Matthew E. Kahn[a], Kamiar Mohaddes[b†], Ryan N. C. Ng[c], M. Hashem Pesaran[ad], Mehdi Raissi[e] and Jui-Chung Yang[f]

[a] Department of Economics, University of Southern California, USA; [b] Judge Business School & King's College, University of Cambridge, UK; [c] Faculty of Economics, University of Cambridge, UK; [d] Trinity College, Cambridge, UK; [e] International Monetary Fund, Washington DC, USA; [f] Department of Economics, National Taiwan University, Taiwan

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Abstract

We study the *long-term* impact of climate change on economic activity across countries, using a stochastic growth model where productivity is affected by deviations of temperature and precipitation from their long-term moving average historical norms. Using a panel data set of 174 countries over the years 1960 to 2014, we find that per-capita real output growth is adversely affected by persistent changes in the temperature above or below its historical norm, but we do not obtain any statistically significant effects for changes in precipitation. We also show that the marginal effects of temperature shocks vary across climates and income groups. Our counterfactual analysis suggests that a persistent increase in average global temperature by 0.04°C per year, in the absence of mitigation policies, reduces world real GDP per capita by more than 7 percent by 2100. On the other hand, abiding by the Paris Agreement goals, thereby limiting the temperature increase to 0.01°C per annum, reduces the loss substantially to about 1 percent. These effects vary significantly across countries depending on the pace of temperature increases and variability of climate conditions. The estimated losses would increase to 13 percent globally if country-specific variability of climate conditions were to rise commensurate with annual temperature increases of 0.04°C.

JEL Classifications: C33, O40, O44, O51, Q51, Q54.

Keywords: Climate change, economic growth, adaptation, counterfactual analysis.

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†Corresponding author. Email address: km418@cam.ac.uk.

1 Introduction

Global temperatures have increased significantly in the past half century and extreme weather events, such as cold snaps and heat waves, droughts and floods, as well as natural disasters, are becoming more frequent and severe; see IPCC (2021). These changes in the distribution of weather patterns (i.e., climate change[1]) are not only affecting low-income countries and emerging markets, but also advanced economies—in September 2017 while Los Angeles experienced the largest fire in its history, Hurricanes Harvey and Irma caused major destruction in Texas and Florida, respectively. A persistent rise in temperatures, changes in precipitation patterns and/or more volatile weather events can have long-term macroeconomic effects by adversely affecting labour productivity, slowing investment and damaging human health.

This paper investigates the *long-term* macroeconomic effects of weather patterns transformed by climate change across 174 countries over the period 1960 to 2014. While weather could affect the level of output across climates, for example, by changing agricultural yields, climate change, by shifting the long-term average and variability of weather, could impact an economy's ability to grow in the long-term, through reduced investment and lower labour productivity. We focus on both of these issues and develop a theoretical growth model that links deviations of temperature and precipitation (weather) from their long-term moving-average historical norms (climate) to per capita real output growth (Appendix A.1).

In our empirical application, we allow for dynamics and feedback effects in the interconnections of climatic and macroeconomic variables, distinguish between level and growth effects—including for long-term—, consider asymmetric weather effects, and test for differential impact of weather shocks across climates. Also, by using deviations of temperature and precipitation from their respective historical norms, while allowing for nonlinearity[2] and an implicit model for adaptation, we avoid the econometric pitfalls associated with the use of trended variables, such as temperature, in output growth equations. As it is well known, and is also documented in our paper, temperature has been trending upward strongly in almost all countries in the world, and its use as a regressor in growth regressions can lead to spurious results. A detailed analysis of how trends in temperature can lead to spurious trends in output growth in regressions used in the literature is provided in Appendix A.2.

The literature which attempts to quantify the effects of weather and/or climate on economic performance (agricultural production, labour productivity, commodity prices, health, conflict, and economic growth) is growing fast—see Stern (2007), IPCC (2014), Hsiang

[1] Weather refers to atmospheric conditions over short periods of time (e.g., temperature and precipitation). Climate refers to the long-term average and variability of weather. Climate change is a shift "in the state of the climate that can be identified (e.g., via statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer" (IPCC (2014)).

[2] Non-linearity arises because growth is only affected when temperature (or precipitation) goes above or below a time-varying and country-specific historical threshold (i.e., the norm). It is due to this feature that future growth is affected not only by warming (or cooling if that was the case) but also by its variability.

(2016), Cashin et al. (2017), Letta and Tol (2019) and the recent surveys by Tol (2009), Dell et al. (2014), and Tol (2018). There are a number of grounds on which the econometric evidence of climate impacts on the economy may be questioned. Firstly, the earlier literature which relied on the cross-sectional approach (e.g., Sachs and Warner 1997, Gallup et al. 1999, and Nordhaus 2006) was hindered by the temporal invariance of climate over the studied time-frames and by important omitted variables that affect economic performance (e.g., institutions). The more recent literature uses panel data models to estimate the economic effects of weather shocks. See, for example, Burke et al. (2015), Dell et al. 2009, Dell et al. (2012), Dell et al. (2014), and Hsiang (2016). There is, however, some disagreement in the literature as to whether temperature affects the level of economic output or its growth. See Schlenker and Auffhammer (2018) and Newell et al. (2021) for a discussion.

Secondly, econometric specifications of the weather–macroeconomic relation are often written in terms of GDP per capita growth and the level of temperature, T_{it}, and in some cases also T_{it}^2;[3] see, for instance, Dell et al. (2012), Burke et al. (2015), and Kalkuhl and Wenz (2020). But if T_{it} is trended, which is the case in almost all countries in the world (see Appendix A.3), its inclusion in the regression will introduce a linear trend in per capita output growth which is spurious and is not supported by the data (see Table A.1), and can in turn lead to biased estimates. The prevalence of this issue in the econometric specifications used in the literature is demonstrated in Appendix A.2. Indeed, Mendelsohn (2016) and Tol (2021) argue that researchers should focus on the deviation of T_{it} from its long-term average to estimate unbiased weather effects in panel data studies. As well, this transformation would allow for an implicit model of adaptation. Also, current panel models do not explicitly model climate variability in the estimation of long-term damage functions.

Thirdly, the fixed effects (FE) estimators used in panel-data studies assume that climate variables are strictly exogenous. At the heart of the Dynamic Integrated model of Climate and the Economy (DICE) model of Nordhaus is the need to account for bi-directional feedback effects between growth and climate change (see Nordhaus 1992). In his work, Nordhaus accounts for the fact that faster economic activity increases the stock of greenhouse gas (GHG) emissions and thereby the average temperature (possibly with a long lag). At the same time, rising average temperature could reduce real economic activity. Consequently, when estimating the impact of temperature on economic growth, T_{it} may not be considered as strictly exogenous, but merely weakly exogenous/predetermined to income growth; in other words economic growth in the past might have feedback effects on future temperature. While it is well known that the FE estimator suffers from small-T bias in dynamic panels (see Nickell 1981) with N (the cross-section dimension) larger than T (the time series dimension), Chudik et al. 2018 show that this bias exists regardless of whether the lags of the

[3] It is argued that this quadratic specification would account for the global nonlinear relationship between temperature and growth; i.e., a common temperature threshold.

dependent variable are included or not, so long as one or more regressors are not strictly exogenous. In such cases, inference based on the standard FE estimator will be invalid and can result in large size distortions unless $N/T \to 0$, as $N, T \to \infty$ jointly.

We contribute to the literature along the following dimensions. Firstly, we explicitly model and test for level or growth effects of weather shocks and estimate the long-term macroeconomic impact of persistent increases in temperature. Secondly, we use the half-panel Jackknife FE (HPJ-FE) estimator proposed in Chudik et al. (2018) to deal with the possible bias and size distortion of the commonly-used FE estimator (given that T_{it} is weakly exogenous). When the time dimension of the panel is moderate relative to N, the HPJ-FE estimator effectively corrects the Nickel-type bias if regressors are weakly exogenous, and is robust to possible feedback effects from aggregate economic activity to the climate variables. Thirdly, we test the predictions of our theoretical growth model using cross-country data on per-capita GDP growth and deviations of temperature and precipitation from their moving average historical norms over the past fifty-five years (1960–2014). Our focus on "deviations" is a departure from the literature, as changes in the distribution of weather patterns (not only averages of temperature and precipitation but also their variability) are modeled explicitly; an implicit model of adaptation is introduced; and the econometric pitfalls of including trended variables (that is, T_{it}) in growth regressions are avoided (see Appendix A.2 for details). Moreover, rather than assuming a common climate threshold across countries, we allow for country-specific and time-varying climate thresholds and also test for asymmetric effects.[4] Finally, we estimate the differential impact of weather shocks across climates (e.g., hot and cold) and income groups (rich and poor) using a heterogenous panel data model.

Our results suggest that a series of positive (or negative) weather shocks has a long-term negative effect on per capita GDP growth. Since we are measuring an integral of marginal weather effects in our regressions, we can cautiously link them to climate change. Specifically, we show that if temperature rises (falls) above (below) its historical norm by 0.01°C annually for a long period of time, income growth will be lower by 0.0543 percentage points per year. We could not detect any significant evidence of an asymmetric long-term growth impact from persistent positive and negative deviations of temperature from its norms. Furthermore, we show that our empirical findings pertain to poor or rich, and hot or cold countries alike (albeit to varying degrees) as economic growth is affected not only by persistent increases in temperatures (and the pace with which they are rising) but also by the degree of climate

[4] Assuming common climate thresholds, as is done in the literature, leads to important oddities in individual country estimates. For example, Burke et al. (2015) estimate that per capita GDP will be 63, 210, 247, 419, 516, 1413 percent larger in Germany, Sweden, Canada, Russia, Finland, and Mongolia as a result of climate change by 2100. Similarly, it is estimated that many countries (including Brazil, India, and most African and South East Asian countries) will experience per capita GDP losses of more than 80 percent which is hard to imagine barring climate disasters (which cannot be modeled within a stochastic growth framework as we document in Appendix A.1). See https://web.stanford.edu/~mburke/climate/map.php for the mentioned individual country results.

variability.[5] One of the reasons that cold countries are also affected by climate change is the faster pace with which temperatures are rising in these regions than in hot countries. Suppose that the pace of temperature increases was the same across hot and cold climates, then our heterogenous panel estimations would suggest a smaller, but still negative, marginal weather effect in cold countries. Most papers in the literature find that temperature increases have had uneven macroeconomic effects, with adverse consequences *only* in countries with hot climates or low-income countries; see, for instance, Sachs and Warner (1997), Jones and Olken (2010), Dell et al. (2012), International Monetary Fund (2017), and Mejia et al. (2018). We estimate that the marginal effects of weather shocks are larger in low-income countries because they have lower capacity to deal with the consequences of climate change. However, this does not mean that rich nations are immune from the effects of climate change.

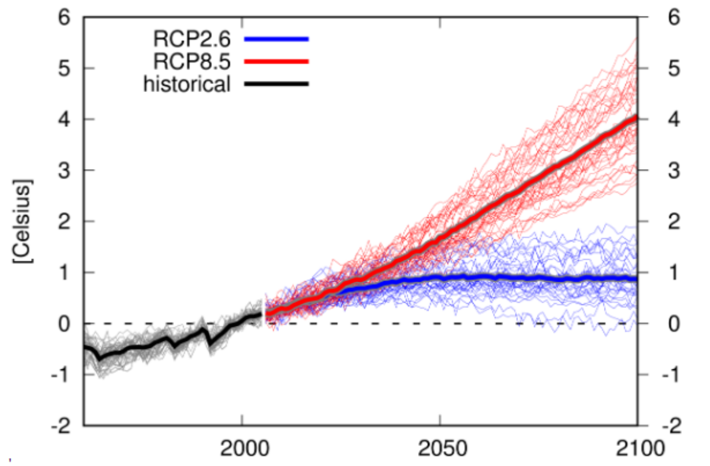
To contribute to climate change policy discussions, we perform a number of counterfactual exercises where we investigate the cumulative income effects of annual increases in temperatures over the period 2015–2100 (when compared to a baseline scenario under which temperature in each country increases according to its historical trend of 1960–2014). We show that an increase in average global temperature of 0.04°C per year—corresponding to the Representative Concentration Pathway (RCP) 8.5 scenario (see Figure 1), which assumes higher greenhouse gas emissions in the absence of mitigation policies—reduces world's real GDP per capita by 7.22 percent by 2100. The estimated losses under the RCP 8.5 scenario would almost double (to 13.11 percent globally by 2100) if country-specific variability of climate conditions were to rise commensurate to temperature increases (see Figure 2 and Table 7). Limiting the increase to 0.01°C per annum, which corresponds to the December 2015 Paris Agreement objective, reduces the output loss substantially to 1.07 percent.[6]

To put our results into perspective, Figure 2 compares our economic loss estimates with those from select papers in the literature. Our counterfactual estimates are relatively large. They suggest that all countries would experience a fall in GDP per capita by 2100 in the absence of climate change policies (i.e., under a high-emission scenario or RCP 8.5). However, the size of these income effects varies across countries and regions depending on the pace with which temperatures increase over the century and the historical variability of climate conditions in each country and their evolution going forward (see Figures 3, 6 and 7); for instance, for the U.S. the losses are relatively large at 10.52 percent under the RCP 8.5

[5] For example, while the level of temperature in Canada is low, the country is warming up twice as fast as rest of the world and therefore is being affected by climate change (including from damages to its physical infrastructure, coastal and northern communities, human health and wellness, ecosystems and fisheries).

[6] The Paris Agreement, reached within the United Nations Framework Convention on Climate Change (UNFCCC), aims to keep the increase in the global average temperature to below 2 degrees Celsius above pre-industrial levels over the 21st century. The average global temperature is already 1°C above the pre-industrial levels. For most countries, the Nationally Determined Contributions pledged under the Paris Agreement are deemed insufficient to meet either the 1.5°C or the 2°C target, and, judging by current policies, unlikely to be met in the first place.

Figure 1: Global Temperature Projections (Deviations from 1984-2014)



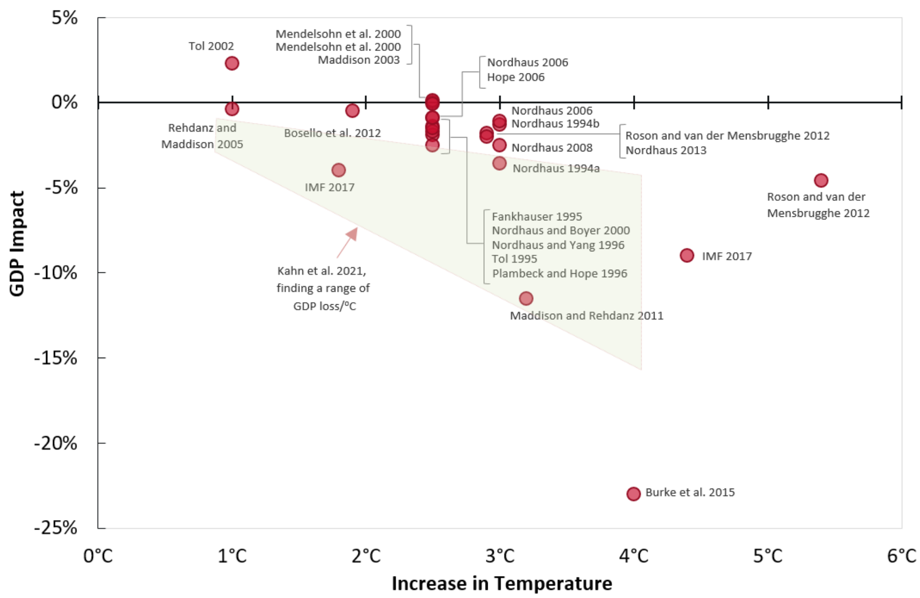
Source: Intergovernmental Panel on Climate Change (IPCC) Coupled Model Intercomparison Project Phase Five AR5 Atlas Subset.
Notes: The thin lines represent each of the 40 models in the IPCC WG1 AR5 Annex I Atlas. The thick lines represent the multimodel mean. Representative Concentration Pathways (RCP) are scenarios of greenhouse gas concentrations, constructed by the IPCC. RCP 2.6 corresponds to the Paris Agreement which aims to hold the increase in the global average temperature to below 2 degrees Celsius above pre-industrial levels. RCP 8.5 is an unmitigated scenario in which emissions continue to rise throughout the 21st century.

scenario in year 2100 (reflecting a sharp increase in its average temperatures), but would be limited to 1.88 percent under the Paris Agreement objective. Moreover, the speed with which the historical norms change (20-, 30-, or 40-year moving averages)—that is how fast countries adapt to global warming or new climate conditions— affects the size of income losses.[7] Overall, while adaptation to climate change can reduce these negative long-run growth effects, it is highly unlikely to offset them entirely.

The rest of the paper is organized as follows. Section 2 discusses the long-run macroeconomic effects of weather patterns transformed by climate change. Counterfactuals in Section 3 investigate the cumulative income effects of annual increases in temperatures under an unmitigated path as well as the Paris Agreement objective up to the year 2100. Section 4 concludes. The paper also contains four appendices. Appendix A.1 develops a multi-country stochastic growth model with weather and climate effects. Appendix A.2 discusses a number of key growth regressions used in macroeconomy-climate research, and how they relate to our approach. Appendix A.3 provides detailed evidence on the historical patterns of climate change across 174 countries. Finally, Appendix A.4 provides additional empirical results.

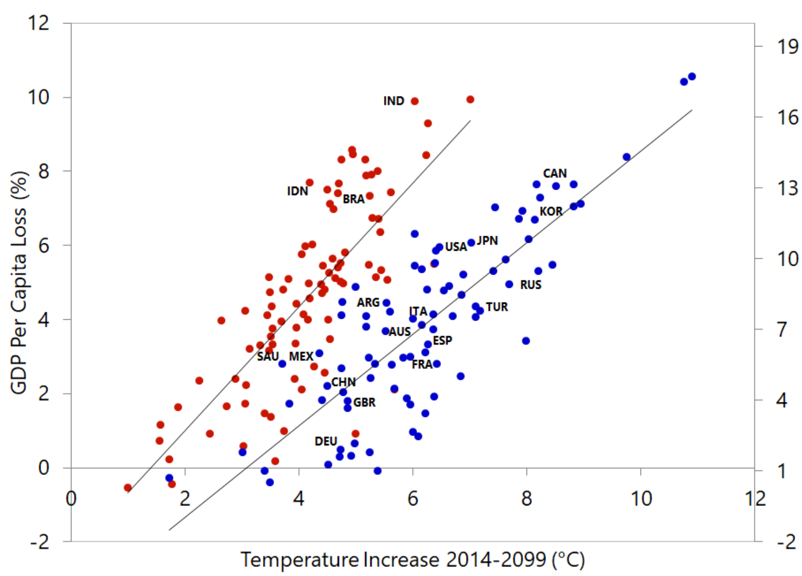
[7] Another way to assess adaptation is to test how the elasticity of per capita GDP to climate variables evolve over time.

Figure 2: GDP Impact of Increases in Temperature



Sources: Tol (2009), Tol (2014), Burke et al. (2015), International Monetary Fund (2017) and authors' estimates (shown as the grey area in the chart).
Notes: Projected GDP impact is for some future year, typically 2100. The shaded area represents the GDP per capita losses from our counterfactual exercise in Section 3 with the upper bound based on $m = 20$ and the lower bound based on $m = 40$ (with increased climate variability). See Tables 6 and 7 for details.

Figure 3: GDP Per Capita Losses from Increases in Temperature: Cold vs. Hot



Notes: GDP per capita losses by 2100 from our baseline counterfactual exercise in Section 4 for hot (on left axis and in red) and cold (on right axis and in blue) countries.

2 Empirical Results

In the empirical application, we use annual population-weighted climate data and real GDP per capita. For the climate variables we consider temperature (measured in degrees Celsius, °C) and precipitation (measured in meters). We construct population-weighted climate data for each country and year between 1900 and 2014 using the terrestrial air temperature and precipitation observations from Matsuura and Willmott (2015) (containing 0.5 degree gridded monthly time series), and the gridded population of the world collection from CIESIN (2016), for which we use the population density in 2010. We obtain the real GDP per capita data between 1960 and 2014 from the *World Development Indicators* database of the World Bank. Combining the GDP per capita and the climate data, we end up with an unbalanced panel, which is very rich both in terms of the time dimension (T), with maximum $T = 55$ and average $T \approx 39$, and the cross-sectional dimension (N), containing 174 countries.

2.1 Long-Term Impact of Climate Change on Economic Growth

Considering strong evidence of an upward trend in temperatures worldwide (see Appendix A.3), and guided by the theoretical growth model with weather and climate variables in Appendix A.1, we base our empirical analysis on the following panel ARDL model:

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell' \Delta \tilde{\mathbf{x}}_{i,t-\ell}(m) + \varepsilon_{it}, \tag{1}$$

where y_{it} is the log of real GDP per capita of country i in year t, a_i is the country-specific fixed effect, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left(\frac{2}{m+1}\right)\left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms per annum, T_{it} and P_{it} are the population-weighted average temperature and precipitation of country i in year t, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation over the preceding m years in each t. Climate norms are typically computed using 30-year moving averages (see, for instance, Arguez et al. 2012 and Vose et al. 2014), but to check the robustness of our results, we also consider historical norms computed using moving averages with $m = 20$ and 40. With $\tilde{T}_{it}(m)$ and $\tilde{P}_{it}(m)$ separated into positive and negative values, we account for the potential asymmetrical effects of climate change on growth around the threshold. The (average) long-run effects, θ, are calculated from the OLS estimates of the short-run coefficients in equation (1): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p}\boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p}\varphi_\ell$.

The reasons for using ARDL growth regressions in deviations form (i.e., temperature and precipitation relative to their long-term moving average historical norms), rather than in levels and/or squares of climate variables, are discussed in some detail in Appendix A.2, where it is shown that including T_{it} and T_{it}^2 will introduce trends in Δy_{it}, which is not present in the data. As documented in Table A.1, we find that at the 5% significance level, output growth is upward trended in only 21 countries out of 174 under consideration, and in fact 9 (174×0.05) of the 21 countries with statistically significant trend coefficients could have arisen by pure chance given the large number of multiple tests being carried out.

Other important econometric considerations behind the use of ARDL regressions are set out in Pesaran and Smith (1995), Pesaran (1997), and Pesaran and Shin (1999) who show that the traditional ARDL approach can be used for long-run analysis; it is valid regardless of whether the underlying variables are $I(0)$ or $I(1)$; and it is robust to omitted variables bias and bi-directional feedback effects between economic growth and its determinants. These features of the panel ARDL approach are clearly appealing in our empirical application. For validity of this technique, however, the dynamic specification of the model needs to be augmented with a sufficient number of lagged effects so that regressors become weakly exogenous. Specifically, Chudik et al. (2016), show that sufficiently long lags are necessary for the consistency of the panel ARDL approach.[8] Since we are interested in studying the growth effects of climate change (a long-term phenomenon), the lag order should be long enough, and as such we set $p = 4$ for all the variables/countries. Using the same lag order across all the variables and countries help reduce the possible adverse effects of data mining that could accompany the use of country and variable specific lag order selection procedures such as Akaike or Schwarz criteria. Note also that our primary focus here is on the long-run estimates rather than the specific dynamics that might be relevant for a particular country.

Table 1 presents the estimation results for two specifications of the panel ARDL regression in (1) and different adaptation speeds ($m = 20, 30$ and 40). We report the fixed effects (FE) estimates of the long-run impact of changes in temperature and precipitation variables on GDP per capita growth ($\widehat{\theta}$), and the estimated coefficients of the error correction term ($\widehat{\phi}$) in columns (a). When the cross-sectional dimension of the panel is larger than the time dimension (in our panel, $N = 174$ and the average $T \approx 38$, see Table 1), the standard FE estimator suffers from small-T bias regardless of whether the lags of the dependent variable are included or not, so long as one or more of the regressors are not strictly exogenous (see Chudik et al. 2018). Since the lagged values of growth and temperature/precipitation can be correlated with the lagged values of the error term ε_{it}, the regressors (climate variables) are weakly exogenous, and hence, inference based on the standard FE estimator is invalid and can result in large size distortions. To deal with these issues, we use the half-panel Jackknife FE (HPJ-FE) estimator of Chudik et al. (2018) and report the results in columns (b) of Table 1 alongside the estimated coefficients of the error correction term ($\widehat{\phi}$). The jackknife bias correction requires $N, T \to \infty$, but it allows T to rise at a much slower rate than N.

Specification 1 of Table 1 for $m = 30$ reports the baseline results. The FE and HPJ-FE

[8] See also Chudik et al. (2013) and Chudik et al. (2017).

Table 1: Long-Run Effects of Climate Change on per Capita Real GDP Growth, 1960–2014

	Specification 1						Specification 2					
	$m = 20$		$m = 30$		$m = 40$		$m = 20$		$m = 30$		$m = 40$	
	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE
$\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^+}$	-0.373***	-0.566***	-0.583***	-0.894***	-0.701***	-1.072***	-0.378**	-0.572***	-0.586***	-0.908***	-0.709***	-1.105***
	(0.141)	(0.209)	(0.195)	(0.291)	(0.248)	(0.373)	(0.141)	(0.208)	(0.196	(0.290)	(0.249)	(0.3721)
$\widehat{\theta}_{\Delta \tilde{T}_{it}(m)^-}$	-0.441**	-0.500**	-0.699**	-0.783**	-0.834*	-0.909*	-0.451**	-0.508*	-0.712**	-0.806*	-0.851*	-0.954**
	(0.217)	(0.249)	(0.346)	(0.380)	(0.445)	(0.485)	(0.217)	(0.249)	(0.346)	(0.380)	(0.446)	(0.485)
$\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^+}$	-0.0441	-0.312	0.104	0.122	-0.0579	-0.00478	-	-	-	-	-	-
	(0.289)	(0.357)	(0.485)	(0.556)	(0.684)	(0.766)						
$\widehat{\theta}_{\Delta \tilde{P}_{it}(m)^-}$	-0.0715	-0.175	-0.132	-0.320	-0.382	-0.595	-	-	-	-	-	-
	(0.323)	(0.431)	(0.576)	(0.660)	(0.754)	(0.8578)						
$\widehat{\phi}$	0.671***	0.603***	0.671***	0.603***	0.671***	0.602***	0.672***	0.604***	0.671***	0.604***	0.671***	0.604***
	(0.0490)	(0.0448)	(0.0489)	(0.0449)	(0.0489)	(0.0449)	(0.0490)	(0.0449)	(0.0489)	(0.0449)	(0.0488)	(0.0449)
N	174	174	174	174	174	174	174	174	174	174	174	174
$\max T$	50	50	50	50	50	50	50	50	50	50	50	50
avg$T$	38.59	38.36	38.59	38.36	38.59	38.36	38.59	38.36	38.59	38.36	38.59	38.36
$\min T$	2	2	2	2	2	2	2	2	2	2	2	2
$N \times T$	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674

Notes: Specification 1 (the baseline) is given by $\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell' \Delta \tilde{\mathbf{x}}_{i,t-\ell} + \varepsilon_{it}$,where y_{it} is the log of real GDP per capita of country i in year t, $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left(\frac{2}{m+1}\right)\left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms per annum, T_{it} and P_{it} are the population-weighted average temperature and of precipitation country i in year t, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation over the preceding m years. $z^+ = zI(z \geq 0)$, and $z^- = -zI(z < 0)$. The long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (1): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p} \varphi_\ell$. Specification 2 drops the precipitation variables from the baseline model: $\tilde{\mathbf{x}}_{it}(m) = \left[\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-\right]'$. Columns labelled (a) report the FE estimates and columns labelled (b) report the half-panel jackknife FE (HPJ-FE) estimates, which corrects the bias in columns (a). The standard errors are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

estimated coefficients of the precipitation variables, $\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^+}$ and $\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^-}$, are not statistically significant. However, long-run economic growth is adversely affected when temperature deviates from its time-varying historical norm persistently, as $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^+}$ and $\widehat{\theta}_{\Delta\tilde{T}_{it}(m)^-}$ are both statistically significant. The HPJ-FE estimates suggest that a 0.01°C annual increase in the temperature above its historical norm reduces real GDP per capita growth by 0.0577 percentage points per year—calculated as $-0.894\times\left(\frac{2}{m+1}\right)$— and a 0.01°C annual decrease in the temperature below its historical norm reduces real GDP per capita growth by 0.0505 percentage points per year—calculated as $-0.783\times\left(\frac{2}{m+1}\right)$. As expected, the FE estimates (which are widely used in the literature) are smaller than their HPJ-FE counterparts in absolute values.[9] Therefore, bias correction is important, including for the counterfactual exercises in Section 3; otherwise the cumulative effects of climate change could be underestimated.

Since the baseline estimates of deviations of precipitation variables from their historical norms (both above and below) are not statistically significant for $m = 30$, we re-estimate equation (1) without them; setting $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-]'$ in specification 2. The results show that persistent deviations of temperature above or below its historical norm, $\tilde{T}_{it}(m)^+$ or $\tilde{T}_{it}(m)^-$, have negative effects on long-run economic growth. Specifically, the HPJ-FE estimates suggest that a persistent 0.01°C increase in the temperature above its historical norm reduces real GDP per capita growth by 0.0586 percentage points per annum in the long run (being statistically significant at the 1% level)—calculated as $-0.908\times\left(\frac{2}{m+1}\right)$— and a 0.01°C annual decrease in the temperature below its historical norm reduces real GDP per capita growth by 0.0520 percentage points per year (being statistically significant at the 5% level)—calculated as $-0.806\times\left(\frac{2}{m+1}\right)$. To make sure that our results are robust to the choice of historical norms, Table 2 also reports the estimation results with climate norms constructed as moving averages of the past 20 ($m = 20$) and 40 ($m = 40$) years, respectively. As in the case with $m = 30$, we note that the estimated coefficients of the precipitation variables, $\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^+}$ and $\widehat{\theta}_{\Delta\tilde{P}_{it}(m)^-}$, are not statistically significant (specification 1). However, the estimated coefficients of the deviations of temperature from its historical norm are statistically significant in both specifications. The speed of adjustment to long-run equilibrium ($\widehat{\phi}$) is quick in both specifications and for different values of m. However, this does not mean that the effects of changes in $\tilde{T}_{it}(m)^+$ and $\tilde{T}_{it}(m)^-$ are short lived.

As discussed above, estimates of the coefficients of $\tilde{T}_{it}(m)^+$ and $\tilde{T}_{it}(m)^-$ are very similar in magnitude. There is, therefore, little evidence of asymmetry in the long-run relationship between output growth and positive or negative deviations of temperature from its historical norm (or the country-specific threshold). This lack of asymmetry suggests that a simpler specification might be preferred and we therefore re-estimate equation (1) by replac-

[9] Since the half-panel jackknife procedure splits the data set into two halves, for countries with an odd number of time observations, we drop the first observation. Thus, the number of observations in Columns (a) and (b) are somewhat different.

Table 2: Long-Run Effects of Climate Change on per Capita Real GDP Growth, 1960–2014 (Using Absolute Value of Deviations of Climate Variables from their Historical Norm)

	Specification 1						Specification 2					
	$m=20$		$m=30$		$m=40$		$m=20$		$m=30$		$m=40$	
	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE
$\widehat{\theta}_{\Delta\lvert\tilde{T}_{it}(m)\rvert}$	-0.375***	-0.523***	-0.582***	-0.836***	-0.702***	-0.981***	-0.379***	-0.529***	-0.583***	-0.841***	-0.706***	-0.996***
	(0.142)	(0.201)	(0.199)	(0.284)	(0.252)	(0.361)	(0.142)	(0.201)	(0.199)	(0.284)	(0.253)	(0.361)
$\widehat{\theta}_{\Delta\lvert\tilde{P}_{it}(m)\rvert}$	-0.0701	-0.125	-0.0325	-0.131	-0.259	-0.404	-	-	-	-	-	-
	(0.237)	(0.335)	(0.473)	(0.527)	(0.646)	(0.709)	-	-	-	-	-	-
$\widehat{\phi}$	0.671***	0.604***	0.671***	0.604***	0.671***	0.603***	0.672***	0.604***	0.672***	0.604***	0.672***	0.604***
	(0.0489)	(0.0448)	(0.0487)	(0.0449)	(0.0487)	(0.0449)	(0.0489)	(0.0449)	(0.04881)	(0.0449)	(0.0487)	(0.0449)
N	174	174	174	174	174	174	174	174	174	174	174	174
$\max T$	50	50	50	50	50	50	50	50	50	50	50	50
avg$T$	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36
$\min T$	2	2	2	2	2	2	2	2	2	2	2	2
$N \times T$	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674

Notes: Specification 1 (the baseline) is given by $\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \boldsymbol{\beta}'_\ell \Delta\tilde{\mathbf{x}}_{i,t-\ell} + \varepsilon_{it}$,where y_{it} is the log of real GDP per capita of country i in year t, $\tilde{\mathbf{x}}_{it}(m) = [\left|\tilde{T}_{it}(m)\right|, \left|\tilde{P}_{it}(m)\right|]'$, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left(\frac{2}{m+1}\right)\left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms per annum, T_{it} and P_{it} are the population-weighted average temperature and of precipitation country i in year t, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation over the preceding m years in each t. The long-run effects, θ_i , are calculated from the OLS estimates of the short-run coefficients in equation (1): $\boldsymbol{\theta} = \phi^{-1}\sum_{\ell=0}^{p}\boldsymbol{\beta}_\ell$, where $\phi = 1 - \sum_{\ell=1}^{p}\varphi_\ell$. Specification 2 drops the precipitation variable from the baseline model. The standard errors are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

ing $\tilde{\mathbf{x}}_{it}(m) = [\tilde{T}_{it}(m)^+, \tilde{T}_{it}(m)^-, \tilde{P}_{it}(m)^+, \tilde{P}_{it}(m)^-]'$ with $\tilde{\mathbf{x}}_{it}(m) = \left(\left|\tilde{T}_{it}(m)\right|, \left|\tilde{P}_{it}(m)\right|\right)'$. The FE and HPJ-FE results are reported in Table 2. Like our earlier results, permanent deviations of precipitation from their historical norms do not affect long-term growth, but permanent deviations of temperature from their time-varying historical norms have a negative effect on long-run GDP growth, with the magnitudes of the coefficient of $\left|\tilde{T}_{it}(m)\right|$ being similar to those reported for $\tilde{T}_{it}(m)^+$ and $\tilde{T}_{it}(m)^-$ in Table 1. Focusing on Specification 2 with $\tilde{x}_{it}(m) = \left|\tilde{T}_{it}(m)\right|$ and the HPJ-FE estimates (our preferred model and estimator), we observe that $\widehat{\theta}_{\Delta\left|\tilde{T}_{it}(m)\right|}$ is robust to alternative ways of measuring $T^*_{i,t-1}(m)$.

To put our results into perspective, note that models that relate temperature to GDP levels yield income loss estimates that are relatively small—consistent with damage functions embedded in major integrated assessment models (IAMs). Specifically, most such models find that when a poor (hot) country gets 1°C warmer, the level of its GDP per capita falls by 1–3 percent; (ii) when a rich (temperate) country gets 1°C warmer, there is little impact on its economic activity. The IAMs have been extensively used in the past few decades to investigate the welfare effects of temperature increases by relying on aggregation of sector-specific effects, see Tol (2014); they have also been used as tools for policy analyses (including by the Obama administration, see Obama (2017), and at international forums). More recent studies, that relate temperature to GDP growth (possibly nonlinearly), arguably show that a shift to a higher (but nonincreasing) temperature level reduces per capita output growth substantially (with compounding effects over time). For example, Burke et al. (2015) consider a panel specification that includes quadratic climate variables in regressions and detect: (i) non-linearity in the relationship with a universal optimal temperature level of 13°C; (ii) differential impact on hot versus cold countries with opposite sign; and (iii) weak lagged effects—their higher lag order (between 1 and 5) estimates reported in Supplementary Table S2, show that only 3 out of 18 estimates are statistically significant. However, our results show that an increase in temperature above its historical norm for an extended period of time is associated with lower economic growth in the long run—suggesting that a temporary temperature shock will only have short-term growth effects but climate change—by shifting the long-term average and variability of weather—could impact an economy's ability to grow in the long-term. Moreover, the marginal impact of weather shocks are estimated to be larger than most papers in the literature and vary across hot and cold climates. Therefore, our findings call for a more forceful policy response to climate change.

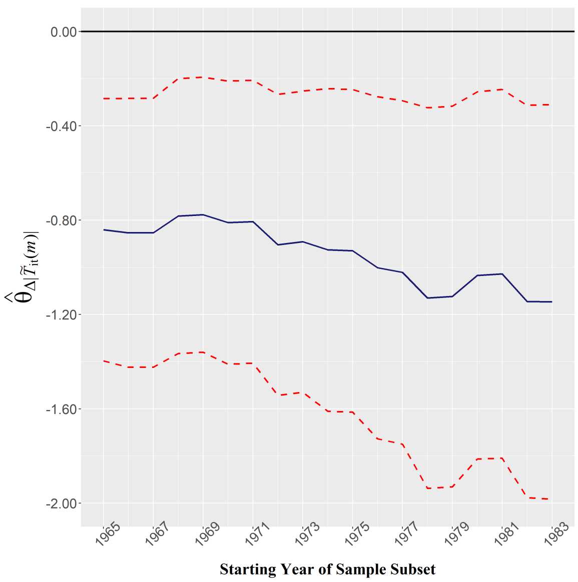
If the world economy were adapting to climate change, ceteris paribus, should we not expect the impact of temperature increases to be shrinking over time? To investigate this hypothesis, we re-estimate our preferred model (with $m = 30$ and $\tilde{x}_{it}(m) = \left|\tilde{T}_{it}(m)\right|$) over different time windows using real GDP per capita growth as the dependent variable. We start with the full sample, 1960–2014, and then drop a year at a time (with the last estimation being carried out for the sub-sample 1983–2014). The results are plotted in Figure 4, showing that the estimated coefficients on $\Delta \left| \tilde{T}_{it-\ell}(m) \right|$ are becoming larger (in absolute value) over time. Do these results cast doubt on the efficacy of adaptation efforts over the last five decades? *Ceteris paribus*, while it is expected that adaptation weakens the relationship between temperature and economic growth over time, we cannot conclude that the world economy has not been adapting to climate change based on Figure 4. First, adaptation efforts might be concentrated in certain countries (typically advanced economies) and certain sectors. Second, it may be the case that adaptation is not keeping pace with the climate change; i.e., global temperatures have increased at an unprecedented pace over the past 40 years. Third, the effects of adaptation might have been offset by structural changes to the economy (that is a shift of value added to sectors that are more exposed to climate change). Fourth, if firms underestimate the likelihood or severity of future weather events, they may not adapt sufficiently; i.e. adaptation technologies are readily available but the take-up so far has been limited by firms. In a survey of private sector organizations across multiple industries within the Organization for Economic Cooperation and Development (OECD) countries, Agrawala et al. (2011) find that only few firms have taken sufficient steps to assess and manage the risks from climate change. Fifth, according to Deryugina and Hsiang (2014) firms tend to under-invest in adaptation owing to its high cost.[10] Overall, the evidence appears to suggest that (at least for now) adaptation has so far had limited impact in dampening the negative effects of climate change globally. But it is possible that with greater public awareness and government efforts, we will be seeing a much faster rate of adaptation in the future. Our analysis is counterfactual given the current state of the world, and outcomes could, and hopefully will, deviate from our counterfactual with better and more forceful environmental polices (both mitigation and adaptation).

2.2 Weather Effects Across Climates and Income Groups

The literature provides evidence for uneven effects of temperature shocks, with worse adverse consequences in economies with hot climates and/or in low-income countries; see, for instance, Sachs and Warner (1997), Jones and Olken (2010), Dell et al. (2012), Burke et al. (2015) and Mejia et al. (2018). In other words, when a rich (temperate) country gets warmer, there will be little impact on its economic activity. There are intuitive reasons and anecdotal evidence for this, including adaptation that has taken place particularly in advanced economies; they are more urbanized and much of the economic activity takes place indoors. For instance, Singapore has attempted to insulate its economy from the heat by extensively engaging in economic activity in places with air conditioning. Therefore, if individuals are aware of how extreme heat affects their economic performance, they can invest in self protec-

[10] Other reasons for underinvestment include knowledge spillovers and networks externalities.

Figure 4: Rolling Estimates of the Long-Run Effects of Temperature Increases on per capita Real GDP Growth



Notes: Figure shows the long-run effects (and their 95% standard error bands) of temperature increases on per capita real GDP growth over different time windows, using the ARDL specification in 1. We start the estimation with the full sample (1960–2014) and then drop one year at a time, ending with the final estimates based on the 1983–2014 sub-sample.

tion to reduce their exposure to such risks.[11] Mendelsohn (2016) also argues that economic effects of weather shocks are likely to be very different in cold versus hot climates.

Given our heterogenous sample of 174 countries and motivated by above studies, an immediate question is whether the estimated adverse long-run growth effects of weather shocks in Specifications 1 and 2 of Table 2 are driven by poor countries. We, therefore, follow Dell et al. (2012) and Burke et al. (2015) and augment Specification 2 with an interactive term, $\Delta\tilde{\mathbf{x}}_{i,t-\ell}(m) \times \mathbb{I}\,(\text{country } i \text{ is poor})$, to capture any possible differential effects of temperature changes from the moving-average norm for the rich and poor countries:

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell' \Delta\tilde{\mathbf{x}}_{i,t-\ell}(m) + \sum_{\ell=0}^{p} \boldsymbol{\zeta}_\ell' \Delta\tilde{\mathbf{x}}_{i,t-\ell}(m) \times \mathbb{I}\,(\text{country } i \text{ is poor}) + \varepsilon_{it}, \tag{2}$$

where, as in Burke et al. (2015), we define country i as poor (rich) if its purchasing-power-parity-adjusted (PPP) GDP per capita was below (above) the global median in 1980. Moreover, to investigate whether temperature increases affect hotter countries more than

[11] For a survey of the literature on heat and productivity, see Heal and Park (2016).

colder ones, we estimated the following panel data model

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \boldsymbol{\beta}_\ell' \Delta \tilde{\mathbf{x}}_{i,t-\ell}(m) + \sum_{\ell=0}^{p} \boldsymbol{\xi}_\ell' \Delta \tilde{\mathbf{x}}_{i,t-\ell}(m) \times \mathbb{I}\left(\text{country } i \text{ is hot}\right) + \varepsilon_{it}, \quad (3)$$

where a country is defined as cold (hot) if its historical average temperature is below (above) the global median. The results from estimating specifications (2) and (3) are reported in Table 3 where the estimated coefficients of the interactive terms are not statistically significant—hence, we cannot reject the hypothesis that there are no differential effects of climate change on poor versus rich nations or hot versus cold countries.

Table 3: Long-Run Effects of Climate Change on per Capita Real GDP Growth of Poor and Hot Countries, 1960–2014 (Using Absolute Value of Deviations of Climate Variables from their Historical Norm)

	Specification 3		**Specification 4**	
$m = 30$	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE
$\widehat{\theta}_{\Delta\lvert\tilde{T}_{it}(m)\rvert}$	-0.551**	-0.836**	-0.754***	-1.029***
	(0.235)	(0.368)	(0.200)	(0.287)
$\widehat{\theta}_{\Delta\lvert\tilde{T}_{it}(m)\rvert\times\mathbb{I}(\ i \text{ is poor})}$	-0.156	-0.137	-	-
	(0.396)	(0.586)	-	-
$\widehat{\theta}_{\Delta\lvert\tilde{T}_{it}(m)\rvert\times\mathbb{I}(\ i \text{ is hot})}$	-	-	0.496	0.562
	-	-	(0.420	(0.656)
$\widehat{\phi}$	0.661***	0.596***	0.672***	0.0605***
	(0.0499)	(0.0469)	(0.0469)	(0.0488)
N	165	165	174	174
max T	50	50	50	50
avg$T$	38.76	38.76	38.36	38.36
min T	8	8	2	2
$N \times T$	6431	6396	6714	6674

Notes: See notes to Table 2. Specifications 3 and 4 interact the temperature variables with dummies for poor and hot countries, respectively (see equations 2 and 3). The standard errors are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

The statistical insignificance of estimated coefficients of the interactive terms in Table 3 may be due to lack of statistical power. In what follows, we attempt to explore the heterogeneity issue further by relying on the half-panel Jackknife Mean Group (MG) estimator in the context of the following heterogenous panel data model:

$$\Delta y_{it} = a_i + \omega_i \Delta \bar{y}_{w,t-1} + \varphi_i \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{i\ell} \Delta \left| \tilde{T}_{it-\ell}\left(m\right) \right| + \varepsilon_{it}. \quad (4)$$

Unlike pooled estimation techniques such as FE where only intercept heterogeneity is taken into account, the above specification allows for the marginal effects of weather shocks to vary across countries or sub-group of countries. Under this more general specification, country-specific marginal effects can be estimated by running least squares regressions for each country i separately, and then considering averages or medians of the estimated coefficients across countries or regions, for example cold versus hot climates, or rich versus poor countries. Pesaran and Smith (1995) show that simple averages of the estimated coefficients (known as mean group, MG, estimates) result in consistent estimates of the underlying population means of the parameters when the time-series dimension of the data is sufficiently large. Whilst it is not possible to be sure about when T is sufficiently large, Monte Carlo evidence suggests that reliable estimates can be obtained with $T \geq 30$ and $N \geq 20$, when output growth is not very persistent, which is the case in our applications. We, therefore, select countries for which we have at least 30 years of observations for GDP growth, resulting in a sample of 130 countries. To explore heterogeneous responses across regions, we define a country as cold if its historical average temperature is among the bottom third of the temperature distribution. Other countries fall into temperate or hot climates. Poor and rich countries are selected based on International Monetary Fund's classifications. The results from estimating equation (4) with and without lagged world output growth, $\Delta\bar{y}_{w,t-1}$, are reported in Table 4. The inclusion of $\Delta\bar{y}_{w,t-1}$ serves two purposes: (1) it accounts for unobserved global factors, and (2) it renders the errors of the regressions across countries weakly (rather than strongly) correlated.

Key findings are as follows: First, the HPJMG estimation results for the sample of all 130 countries are similar (in sign and statistical significance) to those reported in Table 2. Specifically, persistent temperature deviations from their historical norms (owing to climate change) are estimated to have a negative effect on long-run per capita GDP growth (especially when $\Delta\bar{y}_{w,t-1}$ is included as an additional regressor). Second, there is some evidence that negative growth effects of weather shocks are less severe in cold climates. However, the impact of persistent changes in $\left|\tilde{T}_{it}(m)\right|$ on GDP growth in cold climates is still negative, statistically significant, and increasing with m (namely depends on how fast adaptation is taking place). Third, while poor countries are found to be disproportionately affected by weather shocks, rich countries are by no means immune to climate change. Note that lagged world output growth, $\Delta\bar{y}_{w,t-1}$, plays a crucial role in accounting for global output trends that likely interact with global climate conditions. The weather effects are generally weaker when $\Delta\bar{y}_{w,t-1}$ is excluded from regressions.

3 Counterfactual Analysis

We perform a number of counterfactual exercises to measure the cumulative output per capita effects of persistent increases in annual temperatures above their norms (or thresholds) over the period 2015–2100. We carry out this analysis using the HPJ-FE estimates based on the

Table 4: Mean Group Estimates of the Long-Run Effects of Climate Change on per Capita Real GDP Growth, 1960–2014

	Excluding $\Delta \bar{y}_{w,t-1}$			**Including $\Delta \bar{y}_{w,t-1}$**		
Historical Norm:	$m=20$	$m=30$	$m=40$	$m=20$	$m=30$	$m=40$
(a) All 130 Countries						
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.447*	-0.487	-0.521	-0.706***	-0.918**	-1.051**
	(0.2336)	(0.3669)	(0.4734)	(0.2375)	(0.3934)	(0.5188)
$N \times T$	6,198	6,198	6,198	6,020	6,020	6,020
(b) Cold ($\bar{T}_i < 33th$ *Percentile*)						
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.227**	-0.230*	-0.198	-0.238**	-0.342**	-0.457**
	(0.1012)	(0.1279)	(0.1752)	(0.1054)	(0.1509)	(0.1695)
$N \times T$	2,090	2,090	2,090	1,964	1,964	1,964
(c) Temperate or Hot ($\bar{T}_i \geq 33th$ *Percentile*)						
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.665***	-0.780***	-0.613	-0.842***	-1.180***	-1.212**
	(0.1934)	(0.3025)	(0.4308)	(0.2224)	(0.3713)	(0.5039)
$N \times T$	4,108	4,108	4,108	3,990	3,990	3,990
(d) Poor (Low-Income Developing Countries)						
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.603**	-0.759*	-0.855*	-1.020***	-1.463***	-1.703***
	(0.2702)	(0.4059)	(0.4880)	(0.2619)	(0.4289)	(0.5473)
$N \times T$	3,140	3,140	3,140	3,048	3,048	3,048
(e) Rich (Advanced Economies and G20 Emerging Markets)						
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.586***	-0.849***	-1.047***	-0.587***	-1.003***	-1.280***
	(0.1951)	(0.2721)	(0.3734)	(0.2091)	(0.3099)	(0.3922)
$N \times T$	1794	1794	1794	1734	1734	1734

Notes: Specification 1 is given by $\Delta y_{it} = a_i + \varphi_i \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{i\ell} \Delta \left| \tilde{T}_{it-\ell}(m) \right| + \varepsilon_{it},$, where y_{it} is the log of real GDP per capita of country i in year t, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^{*}_{i,t-1}(m)\right]$ is a measure of temperature relative to its historical norm per annum, T_{it} is the population-weighted average temperature of country i in year t, and $T^{*}_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ is the time-varying historical norm of temperature over the preceding m years in each t. Specification 2 is given by $\Delta y_{it} = a_i + \omega_i \Delta \bar{y}_{w,t-1} + \varphi_i \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{i\ell} \Delta \left| \tilde{T}_{it-\ell}(m) \right| + \varepsilon_{it}$, where $\bar{y}_{wt}$ is the log of world's real GDP per capita in year t and the other variables are as before. The models are estimated using the half-panel Jackknife mean-group estimator. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

ARDL specification given by (1), which we write equivalently as

$$\varphi(L)\,\Delta y_{it} = a_i + \beta(L)\Delta x_{it}(m) + \varepsilon_{it},$$

where $x_{it}(m) = \left|T_{it} - T^{*}_{it-1}(m)\right|$, $\varphi(L) = 1 - \sum_{\ell=1}^{4}\varphi_\ell L^l$, $\beta(L) = \sum_{\ell=0}^{4}\beta_\ell L^l$, and L is the lag operator. Pre-multiplying both sides of the above equation by the inverse of $\varphi(L)$ yields

$$\Delta y_{it} = \tilde{a}_i + \psi(L)\Delta x_{it} + \vartheta(L)\varepsilon_{it}, \tag{5}$$

where $\tilde{a}_i = \varphi(1)^{-1}a_i$, $\vartheta(L) = \vartheta_0 + \vartheta_1 L + \vartheta_2 L^2 + \ldots$ and $\psi(L) = \varphi(L)^{-1}\beta(L) = \psi_0 + \psi_1 L + \psi_2 L^2 + \ldots$ for $j = 0, 1, 2, \ldots$.[12]

The counterfactual effects of climate change can now be derived by comparing the output trajectory of country i over the period $T+1$ to $T+h$ under the no change scenario denoted by $b^0_{T_i}$ and $\sigma^0_{T_i}$, with an alternative expected trajectory having the counterfactual values of $b^1_{T_i}$ and $\sigma^1_{T_i}$. Denoting the values of x_{it} for $t = T+1, T+2, ..., T+h$ under these two scenarios by $\mathbf{x}^0_{i,T+1,T+h} = \left\{x^0_{i,T+1}, x^0_{i,T+2}, ..., x^0_{i,T+h}\right\}$, and $\mathbf{x}^1_{i,T+1,T+h} = \left\{x^1_{i,T+1}, x^1_{i,T+2}, ..., x^1_{i,T+h}\right\}$, the counterfactual output change can be written as

$$\xi_{i,T+h} = \mathbb{E}\left(y_{i,T+h}\left|\mathcal{F}_{i,T}, \mathbf{x}^1_{i,T+1,T+h}\right.\right) - \mathbb{E}\left(y_{i,T+h}\left|\mathcal{F}_{i,T}, \mathbf{x}^0_{i,T+1,T+h}\right.\right),$$

where $\mathcal{F}_{iT} = (y_{iT}, y_{i,T-1}, y_{i,T-2}, ...; x_{iT}, x_{i,T-1}, x_{i,T-2}, ...)$. Cumulating both sides of (5) from $t = T+1$ to $T+h$ and taking conditional expectations under the two scenarios we have

$$\xi_{i,T+h} = \sum_{j=1}^{h}\psi_{h-j}\left(x^1_{i,T+j} - x^0_{i,T+j}\right), \tag{6}$$

The impact of climate change clearly depends on the magnitude of $x^1_{i,T+j} - x^0_{i,T+j}$.

We consider the output effects of country-specific average annual increases in temperatures over the period 2015–2100 as predicted under RCP 2.6 and RCP 8.5 scenarios, and compare them with a baseline scenario under which temperature in each country increases according to its historical trend of 1960–2014.[13] However, owing to the non-linear nature of our output-growth specification, changes in trend temperature do not translate on a one-to-one basis to absolute changes in temperature. In line with (A.34), future temperature changes over the counterfactual horizon, $T+j$, $j = 1, 2, ...$ can be represented by

$$T_{i,T+j} = a_{Ti} + b_{Ti,j}\left(T+j\right) + \upsilon_{Ti,T+j}, \text{ for } j = 1, 2, ..., \tag{7}$$

[12] We are suppressing the dependence of x_{it} on m to simplify the exposition.

[13] A similar analysis can also be carried out in terms of changes in precipitation. For brevity and given the empirical results in Section 2, we focus on the counterfactual effects of changes in temperature only.

where we allow for the trend change in the temperature to vary over time. The above equation reduces to (A.34) if we set $b_{Ti,j} = b_{Ti}$ for all j. Suppose also that, as before, the historical norm variable associated with $T_{i,T+j}$, namely $T^*_{i,T+j-1}(m)$, is constructed using the past m years. Then it is easy to show that

$$T_{i,T+j} - T^*_{i,T+j-1}(m) = \left(\frac{m+1}{2}\right) b_{Ti,j} + \left(v_{Ti,T+j} - \bar{v}_{Ti,T+j-1,m}\right),\ j = 1, 2, ..., h, \tag{8}$$

where $\bar{v}_{Ti,T+j-1,m} = m^{-1} \sum_{s=1}^{m} v_{Ti,T+j-s}$. The realised values of $\left|T_{i,T+j} - T^*_{i,T+j-1}(m)\right|$ depend on the probability distribution of weather shocks, $v_{Ti,T+j}$, as well as the trend change in temperature, given by $b_{Ti,j}$. As a first order approximation, and in order to obtain analytic expressions, we assume that temperature shocks, $v_{Ti,T+j}$, over $j = 1, 2, ...$, are serially uncorrelated, Gaussian random variables with zero means and variances, σ^2_{Ti}. Under these assumptions and using the results in Lemma 3.1 of Dhyne et al. (2011), we have

$$\mathbb{E}\left|T_{i,T+j} - T^*_{i,T+j-1}(m)\right| = \mu_{Ti,j}\left[\Phi\left(\frac{\mu_{Ti,j}}{\omega_{Ti}}\right) - \Phi\left(\frac{-\mu_{Ti,j}}{\omega_{Ti}}\right)\right] + 2\omega_{Ti}\phi\left(\frac{\mu_{Ti,j}}{\omega_{Ti}}\right) = g_{Ti}(m, b_{Ti,j}, \sigma_{Ti}) \tag{9}$$

where $\Phi(.)$ and $\phi(.)$ are the cumulative and density distribution functions of a standard Normal variate, respectively, and

$$\mu_{Ti,j} = \left(\frac{m+1}{2}\right) b_{Ti,j}, \text{ and } \omega^2_{Ti} = \sigma^2_{Ti}\left(1 + \frac{1}{m}\right).$$

It is clear from the above expressions that the responses of our climate variables to a postulated rise in temperature most crucially depend on the volatility of temperature around its trend, σ_{Ti}, which differs markedly across countries.[14]

For the baseline scenario, we set $m = 30$ and consider the following counterfactual *country-specific* changes in the trend temperature over the period $T + j$, for $j = 1, 2, ..., H$, as compared to the historical trend rise in temperature (namely b^0_{Ti}):

$$b^1_{Ti,j} = T_{i,T+j} - T_{i,T+j-1} = b^0_{Ti} + jd_i, \text{ for all } j = 1, 2..., H, \tag{10}$$

where d_i is the average incremental change in the trend rise in temperature for country i. We set d_i to ensure that the average rise in temperature over the counterfactual period in country i is equal to the hypothesised value of b^1_{Ti}, and note that

$$b^1_{Ti} = H^{-1}\sum_{j=1}^{H} b^1_{Ti,j} = H^{-1}\sum_{j=1}^{H}\left(T_{i,T+j} - T_{i,T+j-1}\right) = \frac{T_{i,T+H} - T_{i,T}}{H}, \tag{11}$$

[14] For estimates of σ_{Ti} across countries see Table A.7.

where $T_{i,T+H}$ denotes the level of temperature at the end of the counterfactual period. Averaging (10) over j we have

$$d_i = \frac{2\left(b^1_{Ti} - b^0_{Ti}\right)}{H+1}. \tag{12}$$

In our empirical application we set $T_{i,T+H} = T_{i,2099}$ and $T_{i,T+1} = T_{i,2015}$, with implied $H = 85$. For $T_{i,2099}$, for $i = 1, 2, ..., N$, we consider two sets of values based on IPCC's projections under the RCP 2.6 and RCP 8.5 scenarios (see Table A.7). In effect, this specification assumes that over the counterfactual period temperature in country i increases by jd_i per annum over the period $T+1$ to $T+j$, relative to its historical trend value of b^0_{Ti}.

We also assume that the postulated trend rise in temperature, specified in (10), does not affect the volatility of temperature shocks, and set σ^1_{Ti} to its pre-counterfactual value of σ^0_{Ti} . This is a conservative assumption and most likely will result in an under-estimation of the adverse effects of temperature increases, since one would expect rising temperature to be associated with an increase in volatility.[15] With these considerations in mind, and using (6), the mean counterfactual impact of the temperature change on output is given by

$$\begin{aligned} \Delta_{ih}\left(d_i\right) &= \mathbb{E}\left(y^1_{i,T+h}\left|\mathcal{F}_{i,T}\right.\right) - \mathbb{E}\left(y^0_{i,T+h}\left|\mathcal{F}_{i,T}\right.\right) \\ &= \sum_{j=1}^{h} \psi_{h-j}\left[g_{Ti}(m, b^0_{Ti} + jd_i, \sigma^0_{Ti}) - g_{Ti}(m, b^0_{Ti}, \sigma^0_{Ti})\right], \end{aligned} \tag{13}$$

where we base the estimates of b^0_{Ti} and σ^0_{Ti} on the pre-counterfactual period 1960-2014 (see Table A.7), and use

$$g^1_{Ti}(m, b^1_{Ti,j}, \sigma^0_{Ti}) = \mu^1_{Ti,j}\left[\Phi\left(\frac{\mu^1_{Ti,j}}{\omega^0_{Ti}}\right) - \Phi\left(\frac{-\mu^1_{Ti,j}}{\omega^0_{Ti}}\right)\right] + 2\omega^0_{Ti}\phi\left(\frac{\mu^1_{Ti,j}}{\omega^0_{Ti}}\right), \tag{14}$$

$$g^0_{Ti}(m, b^0_{Ti}, \sigma^0_{Ti}) = \mu^0_{Ti}\left[\Phi\left(\frac{\mu^0_{Ti}}{\omega^0_{Ti}}\right) - \Phi\left(\frac{-\mu^0_{Ti}}{\omega^0_{Ti}}\right)\right] + 2\omega^0_{Ti}\phi\left(\frac{\mu^0_{Ti}}{\omega^0_{Ti}}\right), \tag{15}$$

$$\mu^1_{Ti,j} = \left(\frac{m+1}{2}\right)\left(b^1_{Ti,j}\right), \; \mu^0_{Ti} = \left(\frac{m+1}{2}\right) b^0_{Ti}, \tag{16}$$

and $\omega^0_{Ti} = \sigma^0_{Ti}\left(1 + \frac{1}{m}\right)^{1/2}$. To obtain $\left\{\hat{\psi}_j\right\}$, we use the HPJ-FE estimates of $\{\boldsymbol{\beta}_\ell\}^4_{l=0}$ and $\{\varphi_l\}^4_{l=1}$ from the ARDL equation with $\left|T_{it} - T^*_{i,t-1}(m)\right|$ as the climate variable. These estimates and their standard errors are reported in Table 5. Figure 5 plots the estimates of ψ_j for $j = 0, 1, 2, \ldots, 20$, for which the estimated mean lag is $\frac{\sum_{j=1}^{\infty} j\hat{\psi}_j}{\sum_{j=0}^{\infty} \hat{\psi}_j} = 3.1943$ years.

We report the real GDP per capita losses from global warming under the RCP 2.6 and RCP 8.5 scenarios, compared to the reference case, in country heat maps and for the year 2100 only, but make all of the 174 country-specific estimates over various horizons (by year

[15] Moreover, accounting for international spillover effects of climate change, individual countries' long-term growth effects could be larger.

Table 5: Effects of Climate Change on per Capita Real GDP Growth, 1960–2014

$\widehat{\beta}_0$	-0.0038*	$\widehat{\varphi}_1$	0.2643***	No. of Countries (N)	174
	(0.0021)		(0.0500)	$\max T$	50
$\widehat{\beta}_1$	-0.0056*	$\widehat{\varphi}_2$	0.0785***	avg$T$	38.36
	(0.0029)		(0.0266)	$\min T$	2
$\widehat{\beta}_2$	-0.0084***	$\widehat{\varphi}_3$	0.0547**	No. of Obs. ($N \times T$)	6,674
	(0.0031)		(0.0216)		
$\widehat{\beta}_3$	-0.0090***	$\widehat{\varphi}_4$	-0.0016		
	(0.0026)		(0.0327)		
$\widehat{\beta}_4$	-0.0060***				
	(0.0021)				

Notes: Estimates are based on $\Delta y_{it} = a_i + \sum_{\ell=1}^{4} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{4} \beta_\ell^{'} \Delta x_{i,t-\ell}(m) + \varepsilon_{it}$,where y_{it} is the log of real GDP per capita of country i in year t, $x_{it}(m) = \left|T_{it} - T_{i,t-1}^{*}(m)\right|$, T_{it} is the population-weighted average temperature of country i in year t, and $T_{i,t-1}^{*}(m)$ is the historical temperature norm of country i (based on moving averages of the past 30 years). The coefficients are estimated by the half-panel jackknife FE (HPJ-FE) procedure and the standard errors are based on the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at 1% (***), 5% (**), and 10% (*) levels.

Figure 5: $\{\psi_j\}$ **for** $j = 0, 1, 2, \ldots, 20$

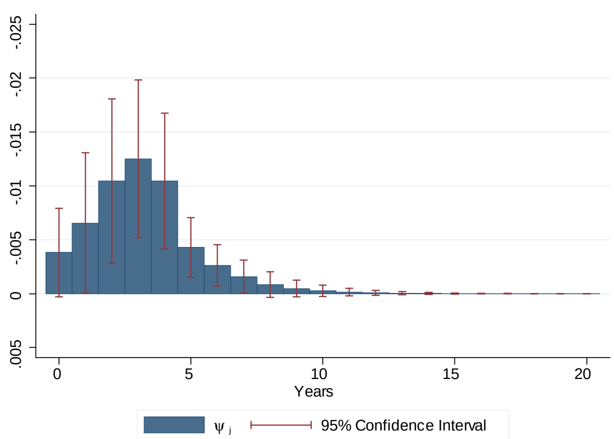


Table 6: Percent Loss in GDP per capita by 2030, 2050, and 2100 under the RCP 2.6 and RCP 8.5 Scenarios

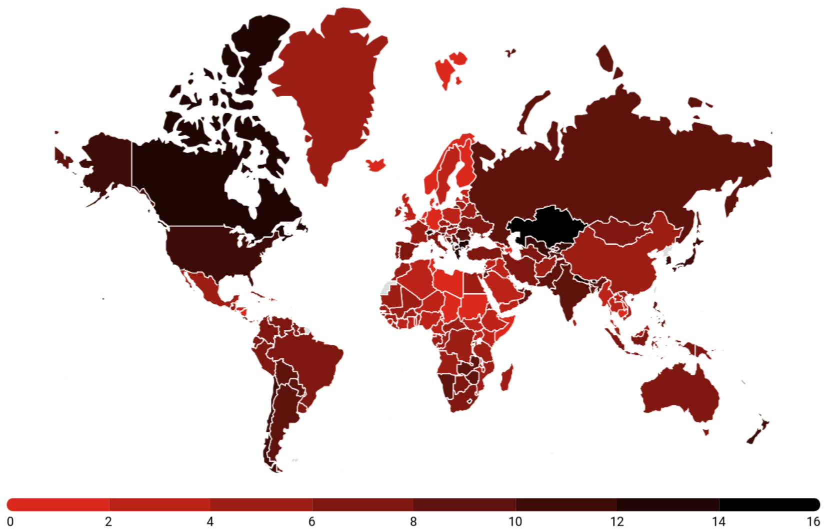
	Year 2030 ($h = 16$)			Year 2050 ($h = 36$)			Year 2100 ($h = 86$)		
	$m = 20$	$m = 30$	$m = 40$	$m = 20$	$m = 30$	$m = 40$	$m = 20$	$m = 30$	$m = 40$
World									
RCP 2.6	-0.01	-0.01	-0.02	0.06	0.11	0.16	0.58	1.07	1.57
RCP 8.5	0.40	0.80	1.25	1.39	2.51	3.67	4.44	7.22	9.96
China									
RCP 2.6	-0.22	-0.45	-0.71	-0.38	-0.80	-1.31	0.24	0.45	0.67
RCP 8.5	0.31	0.58	0.87	0.90	1.62	2.30	2.67	4.35	5.93
European Union									
RCP 2.6	-0.04	-0.08	-0.13	-0.06	-0.13	-0.22	0.05	0.09	0.13
RCP 8.5	0.24	0.50	0.80	0.79	1.53	2.35	2.67	4.66	6.69
India									
RCP 2.6	0.12	0.26	0.42	0.41	0.81	1.27	1.44	2.57	3.69
RCP 8.5	0.60	1.16	1.78	2.13	3.62	5.08	6.37	9.90	13.39
Russia									
RCP 2.6	-0.07	-0.14	-0.23	-0.16	-0.34	-0.56	-0.33	-0.71	-1.19
RCP 8.5	0.51	1.03	1.63	1.62	3.08	4.61	5.28	8.93	12.46
United States									
RCP 2.6	0.10	0.20	0.33	0.29	0.60	0.96	0.98	1.88	2.84
RCP 8.5	0.60	1.20	1.86	2.13	3.77	5.39	6.66	10.52	14.32

Notes: We consider persistent increases in temperatures based on the RCP 2.6 and RCP 8.5 scenarios. Numbers are PPP GDP weighted averages of $\Delta_{ih}(d_i)$, see equation (13), with $h = 16$, 36, and 86 (corresponding to the year 2030, 2050, and 2100, respectively) and $m = 20$, 30, and 40.

2030, 2050, and 2100) available in Table A.7. Figure 6 shows that in the absence of climate change policies (under the RCP 8.5 Scenario with $m = 30$), the percent losses in per-capita incomes by 2100 are sizable, regardless of whether a country is rich or poor, and hot or cold. Nonetheless, the losses vary significantly across countries depending on the country-specific projected paths of temperatures. Figure 7 shows that if we managed to limit the increase in average global temperatures to 0.01°C per annum (the RCP 2.6 scenario), in line with the Paris Agreement objective, we would be able to substantially reduce these losses.

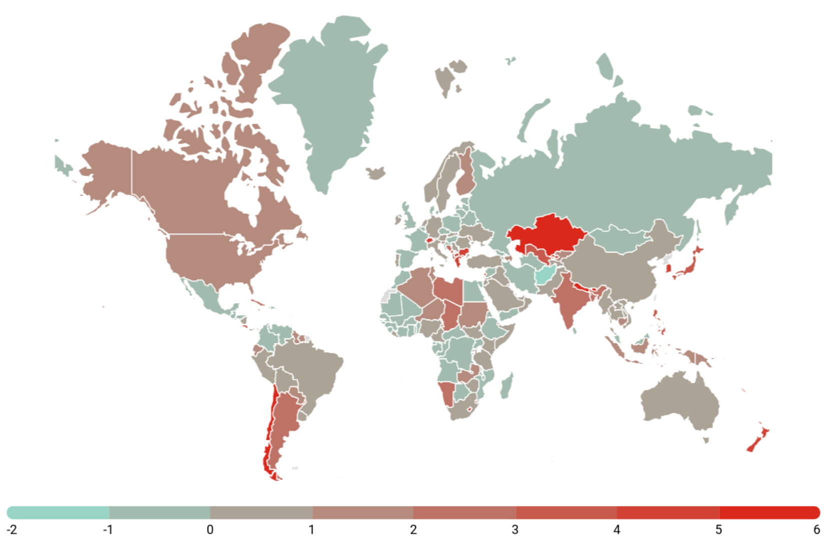
Table 6 reports the real GDP per capita losses for China, the European Union, India, Russia, and the United States, over various time horizons. As in Figure 6, income effects are substantially larger under an unmitigated path (i.e., RCP 8.5). Nonetheless, under both scenarios, the cross-country heterogeneity is significant. Focusing on the RCP 8.5 scenario (with $m = 30$) we observe that the losses vary between 0.50 and 1.20 percent, 1.53 and 3.77

Figure 6: Percent Loss in GDP per capita by 2100 in the Absence of Climate Change Policies (RCP 8.5 Scenario)



Notes: The heat map shows $\Delta_{ih}(d_i)$, see equation (13), in year 2100 with $m = 30$, based on the RCP 8.5 scenario.

Figure 7: Percent Loss in GDP per capita by 2100 Abiding by the Paris Agreement Objective (RCP 2.6 Scenario)



Notes: The heat map shows $\Delta_{ih}(d_i)$, see equation (13), in year 2100 with $m = 30$, based on the RCP 2.6 scenario.

percent, and 4.35 and 10.52 percent in 2030, 2050 and 2100, respectively; with a relatively large impact estimated for the United States in 2100 (reflecting IPCC's projections of a sharp increase in the country's average temperature in the absence of mitigation efforts).

Averaging the losses across countries, using PPP-GDP weights, we report the global income effects of climate change under the RCP 2.6 and RCP 8.5 scenarios in Table 6. Under the Paris agreement objective, and assuming $m = 30$, our results indicate that the world could actually benefit from mitigation policies in year 2030 (compared to a reference case in which temperatures increase according to their historical trends of 1960–2014), while limiting the economic losses of climate change to 0.11 and 1.07 percent over the next 36 and 86 years, respectively. However, a persistent above-norm increase in average global temperature by 0.04°C per year (based on RCP 8.5) leads to substantial output losses, reducing real per capita output by 0.80, 2.51 and 7.22 percent in 2030, 2050 and 2100, respectively. Overall these economic effects are somewhat larger than those obtained in existing studies in the literature and what is generally discussed in policy circles (see Figure 2).

Can adaptation help offset these negative income effects? Repeating the counterfactual exercise for different values of m highlights the role of adaptation. The shorter the m, the faster agents treat higher temperatures as the new norm. Table 6 shows the effects of global warming over time for various values of m. The results indicate that per-capita output losses are lower for $m = 20$ but significantly higher if it takes longer to adapt to climate change ($m = 40$). Overall, we argue that while climate change adaptation could reduce these negative economic effects, it is highly unlikely to offset them entirely. More forceful mitigation policies are needed to limit the damage from climate change.

Table 7: Percent Loss in GDP per capita by 2030, 2050, and 2100 under the RCP 8.5 Scenario: the Role of Climate Variability

	Year 2030 ($h = 16$)	Year 2050 ($h = 36$)	Year 2100 ($h = 86$)
World	2.02	5.18	13.11
China	0.78	1.99	5.02
European Union	1.45	3.71	9.37
India	2.62	6.70	16.92
Russia	2.00	5.13	12.94
United States	2.66	6.81	17.19

Notes: We consider persistent increases in temperatures based on the RCP 8.5 scenario but set $\sigma_{Ti}^{1} = \left(\mu_{Ti,j}^{1}/\mu_{Ti}^{0}\right)\sigma_{Ti}^{0}$. Numbers are PPP GDP weighted averages of $\Delta_{ih}(d_i)$, with $h = 16$, 36, and 86 (corresponding to the year 2030, 2050, and 2100, respectively) and $m = 30$.

We showed that economic growth is affected not only by higher temperatures but also by the degree of climate variability. To study the role of climate volatility in determining

GDP per capita losses, instead of setting $\sigma_{Ti}^1 = \sigma_{Ti}^0$, we allow temperature increases to affect the variability of temperature shocks commensurately. That is, we keep the coefficient of variation unchanged, and therefore set $\sigma_{Ti}^1 = \left(\mu_{Ti,j}^1/\mu_{Ti}^0\right)\sigma_{Ti}^0$. The results are reported in Table 7 for the RCP 8.5 scenario and $m = 30$. As expected, the estimated GDP per capita losses become significantly larger, almost doubling at the global level by 2100 to 13.11 percent. For the United States, the losses are likely to be 70 percent higher compared to the baseline counterfactual scenario reported in Table 6. In terms of the channels of impact, the increase in the degree of climate variability affects economies by reducing labor productivity, increasing health problems (e.g., heat-related health issues or drought-related water and food shortages), damaging infrastructure (e.g., from flooding in river basins and coasts and landslides), and disruptions in supply chains—see IPCC (2014) for details.

4 Concluding Remarks

Using data on 174 countries over the period 1960 to 2014, and a novel econometric strategy (that differentiates between level and growth effects including over the long term; accounts for bi-directional feedbacks between economic growth and climate change; considers asymmetric weather effects; allows for nonlinearity and an implicit model of adaptation; and deals with temperature being trended), we showed that persistent changes in temperature above time-varying norms has long-term negative impacts on economic growth. If temperature deviates from its historical norm by 0.01°C annually for an extended period of time, long-term income growth will be lower by 0.0543 percentage points per year. Furthermore, we illustrated that these negative long-run growth effects are prevalent in all countries but to different degrees across climates and income groups. In particular, our heterogenous panel data estimates suggested a lower marginal weather effects in cold and/or rich countries (i.e., slope coefficients were smaller). Nevertheless, we find that income losses are sizable even in cold climates either because they are warming up much faster than temperate or hot regions or climate variability is becoming more pronounced in line with faster temperature increases.

We performed a number of counterfactual exercises where we investigated the output effects of annual increases in temperatures under mitigated and unmitigated scenarios during 2015–2100. We showed that keeping the increase in the global average temperature to below 2 degrees Celsius above pre-industrial levels as agreed by 190 parties in Paris in December 2015, will reduce global income by 1 percent by 2100. However, an increase in average global temperatures of 0.04°C (corresponding to the RCP 8.5 scenario, which assumes higher greenhouse gas emissions in absence of climate change mitigation policies) reduces world's real GDP per capita by 7 percent by 2100, with the size of these income effects varying significantly across countries depending on the pace of temperature increases and variability of climate conditions in each country. The estimated global per capita GDP losses under a high-emissions scenario with no policy action (that is RCP 8.5) would almost double if country-specific climate variability were to rise commensurate to temperature increases in each country (with global income losses amounting to 13 percent by 2100). Overall, abiding by the Paris Agreement objective would go a long way in limiting economic losses from climate change across almost all countries. We also illustrated that while adaptation to climate change could reduce these negative long-run growth effects, it is highly unlikely to offset them entirely. Therefore, our findings call for more forceful policy responses to the threat of climate change, including more ambitious mitigation and adaptation efforts.

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A Appendices

This section is composed of four appendices. Appendix A.1 provides the economic theory that underlies the growth equation with weather shocks used in our empirical analysis. Appendix A.2 discusses how our specifications and econometric analyses relate to the literature. Appendix A.3 reports historical estimates of trend rises in temperature across 174 countries over the past half century. Appendix A.4 provides individual-country estimates of GDP per capita losses under the RCP 2.6 and RCP 8.5 scenarios over various horizons (by year 2030, 2050, and 2100).

A.1 A Multi-Country Stochastic Growth Model with Weather and Climate Effects

Theoretical growth models generally focus on technological progress and permanent improvements in the efficiency with which factors of production are combined as the main drivers of long-term economic growth, and ignore the possible effects of weather patterns transformed by climate change. Examples include Merton (1975), Brock and Mirman (1972), Donaldson and Mehra (1983), Marimon (1989), and Binder and Pesaran (1999), who have developed stochastic growth models for single economies. We extend this literature and consider the growth process across N countries sharing a common technology but subject to different weather patterns.[16]

Consider a set of economies in which aggregate production possibilities are described by the following production function:

$$Y_{it} = \mathcal{F}\left(\Lambda_{it} L_{it}, K_{it}\right), \tag{A.1}$$

where L_{it} and K_{it} are labour and capital inputs, and Λ_{it} is a scale variable that determines labour productivity in economy i. We suppose that labour productivity is governed by technological factors, as well as by country-specific weather conditions. We consider temperature (T_{it}) and precipitation (P_{it}) as the main weather variables, but assume that labour productivity is affected by these variables only when they deviate from their historical norms (which also serve as country-specific but time-varying thresholds or climates). We express the historical norms by $T^{*}_{i,t-1}(m)$ and $P^{*}_{i,t-1}(m)$, respectively, where m denotes the number of years used in computations. Specifically, we set $T^{*}_{i,t-1}(m) = m^{-1}\sum_{s=1}^{m} T_{i,t-s}$ and $P^{*}_{i,t-1}(m) = m^{-1}\sum_{l=1}^{m} P_{i,t-l}$. In the theoretical derivations that follow we suppose that m is given and fixed, and address the choice of m in Section 2.

The horizon over which the historical norms are formed depends on the degree of adaptation to rising temperatures or precipitation. Small values of m represent high degrees of adaptation. We regard the historical norms as technologically neutral, in the sense that if temperature and precipitation remain close to their historical norms, they are not expected to have any effects on labour productivity. Recent research demonstrates that different regions of the U.S. have acclimated themselves to their own temperature niche. For instance, Heutel et al. (2016) document that heat waves (cold snaps) cause less deaths in warm (cold) places. Moreover, if temperature and

[16] See also Fankhauser and S.J. Tol (2005) and Dietz and Stern (2015) who discuss economic growth models with climate.

precipitation deviate from their historical norms, the marginal effects on labour productivity could be different across climates, depending on the region under consideration. Accordingly, in what follows we also allow for an asymmetry in the effects of deviations from the historical norms on labour productivity, and introduce the following climate threshold variables:

$$\begin{aligned} \left[T_{it}-T^*_{i,t-1}(m)\right]^+ &= \left[T_{it}-T^*_{i,t-1}(m)\right] I\left(T_{it}-T^*_{i,t-1}(m)\geq 0\right), \\ \left[T_{it}-T^*_{i,t-1}(m)\right]^- &= -\left[T_{it}-T^*_{i,t-1}(m)\right] I\left(T_{it}-T^*_{i,t-1}(m)< 0\right), \end{aligned} \tag{A.2}$$

where $I(z)=1$ if $z\geq 0$ and 0, otherwise. Similarly $\left[P_{it}-P^*_{i,t-1}(m)\right]^+$ and $\left[P_{it}-P^*_{i,t-1}(m)\right]^-$ can be defined for precipitation. By distinguishing between positive and negative deviations of the climate variables from their historical norms, we account for potential nonlinear effects of climate change on economic growth around country-specific thresholds.

Specifically, we adopt the following specification of changes in labour productivity in terms of temperature and precipitation:

$$\Lambda_{it} = A_{it}\exp\left(-\boldsymbol{\gamma}_i'\mathbf{x}_{it}(m)\right), \tag{A.3}$$

where A_{it} is the technology factor,

$$\mathbf{x}_{it}(m)=\begin{bmatrix} \left(T_{it}-T^*_{i,t-1}(m)\right)^+ \\ \left(T_{it}-T^*_{i,t-1}(m)\right)^- \\ \left(P_{it}-P^*_{i,t-1}(m)\right)^+ \\ \left(P_{it}-P^*_{i,t-1}(m)\right)^- \end{bmatrix}, \quad \boldsymbol{\gamma}_i=\begin{pmatrix} \boldsymbol{\gamma}_i^+ \\ \boldsymbol{\gamma}_i^- \end{pmatrix}.$$

$\boldsymbol{\gamma}_i^+=(\gamma^+_{iT},\gamma^+_{iP})'$, and $\boldsymbol{\gamma}_i^-=(\gamma^-_{iT},\gamma^-_{iP})'$.

The historical norms can vary over time, but such variations are likely to be small in the short- to medium-term. One could also consider modelling the adverse effects of deviating from climatic norms, by using the quadratic formulation, for example, $\left[T_{it}-T^*_{i,t-1}(m)\right]^2$ instead of the threshold effects $\left(T_{it}-T^*_{i,t-1}(m)\right)^+$ and $\left(T_{it}-T^*_{i,t-1}(m)\right)^-$. But in cases where T_{it} is trended, which is the situation in almost all 174 countries in our sample (see Table A.5 and the discussion in Appendix A.3), the inclusion of $\gamma_i\left[T_{it}-T^*_{i,t-1}(m)\right]^2$ will induce a quadratic trend in equilibrium log per capita output (or equivalently a linear trend in per capita output growth) which is not desirable and can bias the estimates of the growth-climate change equation. Our focus on the deviations of temperature and precipitation from their historical norms marks a departure from the existing literature by implicitly modelling climate variability around country-specific long-term trends as well as adaptation.

We follow the literature and assume that labour input, L_{it}, and technology variables are exogenously given and can be approximated by the following linear processes

$$\log(L_{it}) = l_{i0}+n_i\,t+u_{ilt}, \tag{A.4}$$

$$\log(A_{it}) = \mathrm{a}_{i0} + g_i t + u_{iat}, \tag{A.5}$$

where l_{i0} and a_{i0} are economy-specific initial endowments of labour input and technology; n_i and g_i are the exogenously-determined rates of growth of labour input and technology, respectively; and u_{ilt} and u_{iat} are the stochastic components which could be driven by a combination of demand and supply shocks. Considering the long-run effects of weather patterns transformed by climate change on income growth, we do not attempt to identify such shocks, and assume that

$$\Delta u_{ilt} = -(1-\rho_{il})\, u_{il,t-1} + \varepsilon_{ilt}, \qquad |\rho_{il}| \leq 1,\ \varepsilon_{ilt} \sim iid\,(0, \sigma_{il}^2); \tag{A.6}$$

$$\Delta u_{iat} = -(1-\rho_{ia})\, u_{ia,t-1} + \varepsilon_{iat}, \qquad |\rho_{ia}| \leq 1,\ \varepsilon_{iat} \sim iid\,(0, \sigma_{ia}^2). \tag{A.7}$$

Shocks to labour input, ε_{ilt}, could be correlated with the predictable part of weather conditions. For example, during heat waves, labour supply could fall before recovering in normal times. In such a setting, seasonal or cyclical changes in weather conditions might not have long-run growth effects, but can nevertheless lead to negative short-run correlations between labour input and weather shocks (as workers adapt their schedules to the changing weather conditions). It is, therefore, important to distinguish between short-run effects and the long-term impact of weather shocks transformed by climate change on income growth. The short-run correlation between weather and labour input shocks also renders the weather variable weakly exogenous, with important econometric implications for estimation of long-run growth effects of long-lasting shifts in weather patterns. The stochastic components of labour input and technology could follow unit-root processes. They also could be characterized as cross-sectionally correlated, for example, by common factor representations.

Finally, and most importantly, we assume the following specification for temperature and precipitation variables:

$$\mathbf{x}_{it}(m) = \boldsymbol{\mu}_{im} + \mathbf{v}_{it}(m),\ \mathbf{v}_{it}(m) \sim (\mathbf{0}, \boldsymbol{\Omega}_m), \tag{A.8}$$

where $\boldsymbol{\mu}_{im}$ are country-specific fixed effects representing the mean deviations of temperature and precipitation from their historical means, and $v_{it}(m)$ is the 4×1 vector of weather shocks, which could be correlated across countries. Since temperature and precipitation are measured as deviations from their historical norms in our analysis, they are unlikely to have unit roots or linear trends, although they could display short term drifts when m is relatively large and temperature increases faster than the economy's ability to adapt to the rising temperature or its increased variability (see Section 3). We acknowledge that our reduced form treatment of the temperature and precipitation variables abstract from explicitly modelling the feedback effects of Carbon dioxide (CO_2) emissions (caused by increased economic activity) to the climate variables. This is typically modelled explicitly in integrated assessment models, notably the DICE—see, for example, Nordhaus and Yang (1996), and Nordhaus (2008, 2013, 2017, 2018), and a recent paper by Ikefuji et al. (2019) which provides a stochastic treatment of a climate-economy model. However, we implicitly allow for such feedback effects on the projected future values of temperature and precipitation when we carry out our counterfactual exercises.

Having specified the exogenous processes, we follow Binder and Pesaran (1999) in deriving conditions under which the solution to the stochastic growth model is ergodic (stochastically stable). This property is essential for making long term inference between output per capita, technological innovation and the temperature and precipitation variables. We assume constant returns to scale, and write (A.1) as

$$Y_{it} = \Lambda_{it} L_{it}\, f(\kappa_{it}), \tag{A.9}$$

where κ_{it} denotes the ratio of physical capital to effective units of labour input, that is

$$\kappa_{it} = \frac{K_{it}}{\Lambda_{it} L_{it}}. \tag{A.10}$$

The physical capital stock depreciates in each period at a constant rate δ_i, and obeys the linear law of motion

$$K_{i,t+1} = (1-\delta_i)K_{it} + I_{it}, \qquad \delta_i \in (0,1). \tag{A.11}$$

The model specification is completed by assuming that households' aggregate saving is given by

$$S_{it} = s(\kappa_{it})\, Y_{it}, \tag{A.12}$$

where the saving function, $s(\cdot)$, is assumed to be continuously differentiable and $s_{it} \in (0,\ 1)$. In equilibrium, we have

$$S_{it} = I_{it} = s(\kappa_{it})\, Y_{it}, \tag{A.13}$$

hence

$$K_{i,t+1} = (1-\delta_i)K_{it} + s(\kappa_{it})\, Y_{it}. \tag{A.14}$$

Following the literature, we assume that that $f(\cdot)$ is twice continuously differentiable, is strictly increasing and concave, and satisfies $f(0)=0$, as well as the Inada conditions $\lim_{\kappa\to 0} f^{'}(\kappa) = +\infty$, and $\lim_{\kappa\to\infty} f^{'}(\kappa) = 0$, for any given value of $\kappa_{it} = \kappa$.

The capital accumulation process, (A.14), can then be written as

$$\frac{K_{i,t+1}}{\Lambda_{i,t+1}L_{i,t+1}} \frac{\Lambda_{i,t+1}L_{i,t+1}}{\Lambda_{it}L_{it}} = (1-\delta_i)\frac{K_{it}}{\Lambda_{it}L_{it}} + s(\kappa_{it})\,\frac{Y_{it}}{\Lambda_{it}L_{it}},$$

which upon using (A.9) and (A.10) yields

$$\kappa_{i,t+1} = \exp\left[-\Delta \ln(\Lambda_{i,t+1}L_{i,t+1})\right]\left[(1-\delta_i)\kappa_{it} + s(\kappa_{it})\, f(\kappa_{it})\right]. \tag{A.15}$$

Also, using equations (A.3), (A.4), and (A.5), we have

$$\Delta \ln(\Lambda_{i,t+1}L_{i,t+1}) = \Delta \ln(A_{i,t+1}) + \Delta \ln(L_{i,t+1}) - \boldsymbol{\gamma}_i^{\prime}\Delta \mathbf{x}_{i,t+1}(m) = n_i + g_i + \xi_{i,t+1},$$

where

$$\xi_{i,t+1} = \triangle u_{i,l,t+1} + \triangle u_{i,a,t+1} - \boldsymbol{\gamma}_i^{\prime}\Delta \mathbf{v}_{i,t+1} \tag{A.16}$$

and $u_{i,l,t+1}$, $u_{i,a,t+1}$ and $\mathbf{v}_{i,t+1}$ are defined by (A.6), (A.7) and (A.8), respectively. Hence

$$\frac{\kappa_{i,t+1}}{\kappa_{it}} = \exp\left(-n_i - g_i + \xi_{i,t+1}\right)\left[(1-\delta_i) + \frac{s(\kappa_{it})\, f(\kappa_{it})}{\kappa_{it}}\right].$$

Binder and Pesaran (1999) investigate the conditions under which the above dynamic stochastic non-linear equation has a steady state solution. They show that under standard regularity conditions on the saving rate, $s(\kappa)$, and assuming that $f(\kappa)/\kappa \to 0$, as $\kappa \to \infty$, the limiting distribution of κ_{it} (as $t \to \infty$) is ergodic in its r^{th} moment if $E\left|\xi_{i,t+1}\right|^r < \infty$, and most importantly, if large negative shocks are ruled out, such that

$$F_\xi\left[log(1-\delta_i) - n_i - g_i\right] = 0, \tag{A.17}$$

where $F_\xi(.)$ is the limiting cumulative distribution function of $\xi_{i,t+1}$, defined by (A.16). Since $n_i+g_i+\delta_i$ is relatively small, the above condition is likely to be satisfied for light-tailed distributions such as Gaussian or sub-Gaussian processes, but not when $\xi_{i,t+1}$ is heavy-tailed with a high level of volatility.[17] Suppose now condition (A.17) is met and the production technology is Cobb-Douglas. Then using (A.3), (A.9), (A.5), and (A.8), we have

$$y_{it} = \ln(Y_{it}/L_{it}) \approx y_{i0}^* + g_i t + u_{iat} - \boldsymbol{\gamma}_i' \mathbf{v}_{it}(m), \tag{A.18}$$

where

$$y_{i0}^* = \mathrm{a}_{i0} + \alpha_i \ln(\kappa_{i\infty}) - \boldsymbol{\gamma}_i' \boldsymbol{\mu}_{im},$$

α_i is the exponent of the capital input in economy i's production function; a_{i0} is the initial technological endowment; and $\kappa_{i\infty}$ is the steady state value of κ_{it}—see Binder and Pesaran (1999) for further details. The variations in the steady state value of y_{it} around its trend $(g_i t)$ are determined by technology and weather shocks, u_{iat} and $\mathbf{v}_{it}(m)$, and vary across countries owing to differences in initial endowments, technological (α_i and g_i) and climate conditions, $\boldsymbol{\gamma}_i' \boldsymbol{\mu}_{im}$. The model can also generate a unit root in y_{it} by assuming that $log(A_{it})$ has a unit root, namely by setting $\rho_{ia} = 1$ in (A.7). In this case, the growth rate of per capita output can be written as

$$\triangle\, y_{it} \approx g_i - \boldsymbol{\gamma}_i' \triangle \mathbf{v}_{it}(m) + \varepsilon_{iat}, \tag{A.19}$$

which reduces to the random walk model of output per capita if we abstract from the weather shocks (by setting $\gamma_i = 0$). In equilibrium, the mean per capita output growth is positively affected by technological progress, $g_i > 0$, and negatively impacted by deviations of the temperature and precipitation from their historical norms when $\gamma_i > 0$. This specification has the added advantage that $E(\triangle y_{it})$ does not inherit the strong trend in T_{it}, which the country/global temperatures have been subject to over the past 55 years (see Appendix A.3 and Table A.5).

The above theoretical derivation of output growth process requires that technology and weather

[17] See Ikefuji et al. (2019) who also show that within their stochastic dynamic economy-climate model, heavy-tailed risk is not compatible with power utility, and propose using the Pareto utility function instead.

shocks satisfy the truncation condition in (A.17). However, this condition is unlikely to be met in the presence of rare disaster events considered in the literature by Rietz (1988), Barro (2006, 2009) and Weitzman (2009), among others. To illustrate this point, let's abstract from demand and weather shocks and assume that the only remaining stochastic process, namely technology, has a unit root. Then $\xi_{i,t+1} = \varepsilon_{iat}$ and condition (A.17) reduces to (dropping the subscripts i)

$$F_{\varepsilon}\left[log(1-\delta)-n-g\right] = Pr\left(\varepsilon_t \leq log(1-\delta)-n-g\right) = 0.$$

As in Barro (2009), suppose that $\varepsilon_t = u_t + v_t$, where u_t is $iidN(0,\sigma_u^2)$, and $v_{t+1} = 0$ with probability $1-p$ and $v_{t+1} = log(1-b)$ with probability p, where $p \geq 0$ is the probability of a disaster, and b $(0 < b < 1)$ is its size, measured as the fraction of output lost. Under this formulation

$$\begin{aligned} Pr\left[\varepsilon_t \leq log(1-\delta)-n-g\right] &= (1-p)\Phi\left(\frac{log(1-\delta)-n-g}{\sigma_u}\right) \\ &\quad +p\Phi\left(\frac{log(1-\delta)-n-g-log(1-b)}{\sigma_u}\right), \end{aligned}$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal variate. Also since $log(1-b) \approx -b$, and $log(1-\delta) \approx -\delta$, then the second term of the above expression could be far from zero if $b > \delta$, noting that $n+g$ is likely to be small, around 0.03. Therefore, in situations where $p > 0$, and b is much larger than the rate of capital depreciation, δ, the truncation condition will not be met even if we assume that non-disaster shocks are Gaussian. Consequently, the random walk model of output growth derived in (A.19), and assumed in the literature, might not be compatible with an equilibrium stochastic growth model, and in particular there is no guarantee for κ_{it} to converge to a time-invariant process, required for the validity of the random walk model of per capita output growth. Therefore, we cannot, and do not, claim that our empirical analysis allows for rare disaster events, whether technological or climatic. From this perspective, the counterfactual outcomes that we discuss in Section 3 should be regarded as conservative because they only consider scenarios where the climate shocks are Gaussian, without allowing for rare disasters.

Finally, in a panel data context, $\ln(\kappa_{it})$ can be approximated by a linear stationary process with possibly common factors, which yields the following Auto-Regressive Distributed Lag (ARDL) specification for y_{it}

$$\varphi_i(L)\Delta y_{it} = a_i + b_i(L)\boldsymbol{\gamma}_i' \triangle \mathbf{x}_{it}(m) + \varepsilon_{it}, \tag{A.20}$$

where $i = 1, 2, ..., N$; $t = 1, 2, ..., T$, $\varphi_i(L)$ and $b_i(L)$ are finite order distributed lag functions, a_i is the fixed effect, and ε_{it} is a serially uncorrelated shock.

A.2 Relation to the Literature

This annex explains how our approach to modelling the climate-macroeconomy relationship relates to the rapidly growing empirical literature on the topic. There are three main differences in model specifications: (a) whether temperature affects the level of GDP or its growth, allowing for lagged effects; (b) what functional form should be used for the relationship between output growth and temperature; and (c) how to account for latent factors in panel regressions. We focus on the studies of Dell et al. (2012), Burke et al. (2015), and Kalkuhl and Wenz (2020).

1. Dell et al. (2012)**,** or DJO for short, consider the following dynamic panel data model (equation A1.5 of their online Appendix II):

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p+1} \psi_\ell T_{it-\ell} + \varepsilon_{it}. \tag{A.21}$$

where y_{it} is the log of real GDP per capita of country i in year t, a_i is the country-specific fixed effect, and T_{it} is the population-weighted average temperature of country i in year t. Suppose that

$$T_{it} = a_{Ti} + b_{Ti}t + v_{Ti,t} \tag{A.22}$$

where $b_{Ti} > 0$, $E(v_{Ti,t}) = 0$, and $E(v_{Ti,t}^2) = \sigma_{T_i}^2$. Substituting (A.22) in equation (A.21) yields

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p+1} \psi_\ell \left(a_{Ti} + b_{Ti}(t-\ell) + v_{Ti,t-\ell}\right) + \varepsilon_{it}.$$

Taking expectations, we have

$$E(\Delta y_{it}) = \sum_{\ell=1}^{p} \varphi_\ell E(\Delta y_{i,t-\ell}) + c_i + b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right) t,$$

where $c_i = a_i + a_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right) - b_{Ti}\sum_{\ell=0}^{p+1} \ell\psi_\ell$. To ensure that $E(\Delta y_{it})$ exists, we suppose that the underlying growth processes are stable such that the roots of $1 - \sum_{\ell=1}^{p} \varphi_\ell z^{-i}$ all lie outside of the unit circle. Under this assumption $\left(1 - \sum_{\ell=1}^{p} \varphi_\ell L^\ell\right)^{-1} = \sum_{i=0}^{\infty} a_i L^i$ and we have

$$\begin{aligned} E(\Delta y_{it}) &= \frac{c_i}{1 - \sum_{\ell=1}^{p} \varphi_\ell} + b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right)\left(\sum_{i=0}^{\infty} a_i L^i\right) t \\ &= \frac{c_i}{1 - \sum_{\ell=1}^{p} \varphi_\ell} + b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right)\left(\sum_{i=0}^{\infty} a_i (t-i)\right), \end{aligned}$$

or after some simplifications, we have[18]

$$E(\Delta y_{it}) = \mu_i + \kappa_i t,$$

where

$$\mu_i = \frac{c_i}{1 - \sum_{\ell=1}^{p} \varphi_\ell} - \frac{b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right)\sum_{\ell=1}^{p} \ell\varphi_\ell}{\left(1 - \sum_{\ell=1}^{p} \varphi_\ell\right)^2} \text{ and } \kappa_i = \frac{b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right)}{1 - \sum_{\ell=1}^{p} \varphi_\ell}.$$

It is clear that the stability of the growth process does not, on its own, ensure that the mean growth is stable over time. For the latter, we also need to impose the additional restriction $b_{Ti}\left(\sum_{\ell=0}^{p+1} \psi_\ell\right) =$

[18] Note that $\sum_{i=0}^{\infty} a_i = \left(1 - \sum_{\ell=1}^{p} \varphi_\ell\right)^{-1}$ and $\sum_{i=0}^{\infty} i a_i = \left(1 - \sum_{\ell=1}^{p} \varphi_\ell\right)^{-2} \sum_{\ell=1}^{p} \ell\varphi_\ell$.

0, so that $E(\Delta y_{it})$ is time-invariant. One can obtain a stationary growth process if either $b_{Ti}=0$ (no trend in temperature) and/or $\left(\sum_{\ell=0}^{p+1}\psi_\ell\right)=0$. Under the latter restriction, the long term growth effect of rising temperature is given by

$$E(\Delta y_{it})=\frac{c_i}{1-\sum_{\ell=1}^{p}\varphi_\ell}$$

which is also compatible with $b_{Ti}=0$. In short, to estimate growth regressions with rising temperature one needs to impose $\sum_{\ell=0}^{p+1}\psi_\ell=0$ on equation (A.21).

In the main part of their paper, DJO assume that $\varphi_\ell=0$ and estimate a distributed lagged model after adding region-year fixed effects, δ_{rt}:

$$\Delta y_{irt}=a_{ir}+\delta_{rt}+\sum_{\ell=0}^{L}\rho_\ell T_{ir,t-\ell}+\varepsilon_{irt},\ L=0,1,5,10 \tag{A.23}$$

To investigate conditions under which the inclusion of region-year fixed effects solves the problem of working with trended temperature, we repeat the analysis above, and without loss of generality, for the baseline regressions of DJO for $L=0$:

$$\Delta y_{irt}=a_{ir}+\delta_{rt}+\rho_0 T_{irt}+\varepsilon_{irt}, \tag{A.24}$$

with $T_{irt}=a_{Ti,r}+b_{Ti,r}t+v_{Ti,rt}$, where as before the temperature shocks, $v_{Ti,rt}$, for country i in region r, have zero means and finite variances. Then we have

$$E(\Delta y_{irt})=(a_{ir}+\rho_0 a_{Ti,r})+\delta_{rt}+(\rho_0 b_{Ti,r})\,t.$$

$E(\Delta y_{irt})$ is stationary if $\delta_{rt}+\rho_0 b_{Ti,r}t=0$ for all i,r and t. In turn, this would either require $b_{Ti,r}=0$ (no trend in temperature), a condition which does not hold given the historical data. Otherwise we must have exact cancellation of linear trends in temperature at the regional level with the region-year fixed effects, namely $\delta_{rt}+\rho_0\bar{b}_{Tr}t=0$, for all r, where $\bar{b}_{Tr}=n_r^{-1}\sum_{i=1}^{n_r}b_{Ti,r}$. Under $\delta_{rt}+\rho_0\bar{b}_{Tr}t=0$ the following restricted version of (A.24) needs to be considered for estimation:

$$\Delta y_{irt}=a_{ir}+\rho_0\left(T_{irt}-\bar{b}_{Tr}t\right)+\varepsilon_{irt},$$

or

$$\Delta y_{irt}=a_{ir}+\psi_0 a_{Ti,r}+\rho_0\left(b_{Ti,r}-\bar{b}_{Tr}\right)t+\rho_0 v_{Ti,rt}+\varepsilon_{irt},$$

One can potentially have steady state growth at the regional level but not at the country level, since $E(\Delta y_{irt})=a_{ir}+\rho_0 a_{Ti,r}+\rho_0\left(b_{Ti,r}-\bar{b}_{Tr}\right)t$, and $E(\Delta y_{irt})$ will be stationary if either $\rho_0=0$ (no temperature effects on growth) or $b_{Ti,r}=\bar{b}_{Tr}$, for all r.

2. While the preferred model of DJO featured a linear temperature effect, that of Burke et al. (2015), or BHM for short, considers a quadratic equation, thus allowing for weather warming to boost growth in countries with cold climates and impede growth in countries with hot climates. This quadratic specification results in an optimal annual average temperature for GDP growth of 13°C. Deviations from this number in either direction generates changes in growth of equal magnitude but of opposite signs. Specifically, BHM consider the following model

$$\Delta y_{it} = a_i + \delta_t + \alpha T_{it} + \beta T_{it}^2 + \gamma_i t + \phi_i t^2 + \varepsilon_{it}. \tag{A.25}$$

where δ_t are the country time effects. $\gamma_i t$ and $\phi_i t^2$ are the country-specific linear time trend and quadratic time trend. It is clear that without further restrictions, the mean output growth, $E(\Delta y_{it})$, in BHM's specification will be trended, which as we have argued is neither plausible on theoretical grounds nor supported empirically. But one cannot rule out that the upward trend in the temperature could cancel out—rendering $E(\Delta y_{it})$ without a trend. To investigate this possibility, we run country-specific regressions of output growth on its lagged value and a linear time trend ($\Delta y_{it} = a_i + \varphi_i \Delta y_{i,t-1} + \gamma_i t$), and report the statistical significance of the long-run trend coefficients, $\theta_i = \gamma_i/(1-\varphi_i)$, in Table A.1 for all countries in our sample. We find that at the 5% significance level, output growth is found to be upward trended in only 21 countries out of 174 in our sample and in the rest θ_i is either negative or not statistically different from zero.

Substituting (A.22) in (A.25) and taking expectations yields:

$$E(\Delta y_{it}) = c_i + E(\delta_t) + \left[(\alpha + 2\beta a_{Ti})\,\theta_i + \gamma_i\right] t + \left(\beta b_{Ti}^2 + \phi_i\right) t^2$$

where $c_i = a_i + \alpha a_{Ti} + \beta a_{Ti}^2 + \beta \sigma_{Ti}^2$. There are many types of restrictions that can be imposed to ensure that $E(\Delta y_{it})$ is not trended. Since δ_t is unobserved it seems most appropriate to set $E(\delta_t) = 0$, and then require that

$$(\alpha + 2\beta a_{Ti})\, b_{Ti} + \gamma_i = 0, \text{ and } \beta b_{Ti}^2 + \phi_i = 0, \text{ for all } i. \tag{A.26}$$

A less restrictive set of conditions will be needed if we assume that $E(\delta_t) = \kappa_1 t + \kappa_2 t^2$, which is a fortuitous specification for $E(\Delta y_{it})$ to be trend-free. Under this specification, the following restrictions are needed

$$(\alpha + 2\beta a_{Ti})\, b_{Ti} + \gamma_i = -\kappa_1 \text{ and } \beta b_{Ti}^2 + \phi_i = -\kappa_2, \text{ for all } i. \tag{A.27}$$

These restrictions can be equivalently written as

$$\beta b_{Ti}^2 + \phi_i = \beta b_{Tj}^2 + \phi_j, \text{ for all } i \neq j \tag{A.28}$$

and

$$(\alpha + 2\beta a_{Ti})\, b_{Ti} + \gamma_i = (\alpha + 2\beta a_{Tj})\, b_{Tj} + \gamma_j \text{ for all } i \neq j \tag{A.29}$$

Using the data set of BHM, we estimate equations (A.25) by the fixed effects (FE) estimator, with or without the time effects (TE), linear trends (LT) or quadratic trends (QT). The results are summarized in Table A.2 where in all its columns conditions (A.28) and (A.29) are not imposed correctly because temperature rises have not been uniform across countries.

3. Kalkuhl and Wenz (2020), or KW for short, adds two additional terms to BHM's spec-

Table A.1: Is Output Growth Trended?

Country	$\frac{\hat{\gamma}_i}{(1-\hat{\varphi}_i)}$	Country	$\frac{\hat{\gamma}_i}{(1-\hat{\varphi}_i)}$	Country	$\frac{\hat{\gamma}_i}{(1-\hat{\varphi}_i)}$
Afghanistan	-0.0117	Georgia	0.1060	Oman	-0.5250**
Albania	0.2640	Germany	-0.0400	Pakistan	-0.0439**
Algeria	-0.0423	Ghana	0.1250***	Panama	0.0384
Angola	0.3180	Greece	-0.1400***	Papua New Guinea	0.0167
Argentina	0.0127	Greenland	-0.0779	Paraguay	-0.0282
Armenia	0.2800	Guatemala	-0.0275	Peru	0.0594
Australia	-0.0211	Guinea	-0.0226	Philippines	0.0375
Austria	-0.0681***	Guinea-Bissau	-0.0502	Poland	-0.1260*
Azerbaijan	0.6040	Guyana	0.0774	Portugal	-0.1370***
Bahamas	-0.0703	Haiti	0.1560	Puerto Rico	-0.1210***
Bangladesh	0.1170***	Honduras	-0.0055	Qatar	-0.0590
Belarus	0.3030	Hungary	-0.0992	Romania	0.0112
Belgium	-0.0747***	Iceland	-0.0870*	Russian Federation	0.4340
Belize	-0.0498	India	0.1080***	Rwanda	0.0971
Benin	0.0184	Indonesia	0.0278	Saint Vincent and the Grenadines	0.0237
Bhutan	-0.0377	Iran	-0.0703	Samoa	-0.0060
Bolivia	0.0416	Iraq	-0.0046	Sao Tome and Principe	0.0011
Bosnia and Herzegovina	-2.2610**	Ireland	-0.0209	Saudi Arabia	-0.0272
Botswana	-0.1560**	Israel	-0.0597*	Senegal	0.0488**
Brazil	-0.0462	Italy	-0.1140***	Serbia	-0.1800
Brunei Darussalam	-0.0655	Jamaica	-0.0269	Sierra Leone	0.0549
Bulgaria	0.0837	Japan	-0.1440***	Slovakia	-0.1570
Burkina Faso	0.0366*	Jordan	-0.0673	Slovenia	-0.3550**
Burundi	-0.0929**	Kazakhstan	-0.0861	Solomon Islands	0.0895
Cabo Verde	-0.0492	Kenya	-0.0536	Somalia	0.0391
Cambodia	0.0600	Kuwait	0.1420	South Africa	-0.0409
Cameroon	-0.0228	Kyrgyzstan	0.3570	South Korea	-0.0864**
Canada	-0.0548**	Laos	0.2010***	South Sudan	0.5840
Central African Republic	-0.0487	Latvia	-0.5140	Spain	-0.0880**
Chad	0.1430*	Lebanon	-0.6390***	Sri Lanka	0.0690***
Chile	0.0470	Lesotho	-0.0352	Sudan	0.1160*
China	0.0666	Liberia	0.0664	Suriname	0.1440
Colombia	0.0092	Libya	-2.5570	Swaziland	-0.0377
Comoros	0.0090	Lithuania	-0.2490	Sweden	-0.0349
Congo	-0.0109	Luxembourg	-0.0142	Switzerland	-0.0061
Congo DRC	-0.0132	Macedonia	0.2310	Syria	-0.0644
Costa Rica	-0.0165	Madagascar	0.0172	Tajikistan	0.7840*
Côte d'Ivoire	-0.0507	Malawi	-0.0101	Tanzania	0.1920***
Croatia	-0.3280*	Malaysia	-0.0196	Thailand	-0.0508
Cuba	0.0335	Mali	-0.0160	Togo	-0.0652
Cyprus	-0.2440***	Mauritania	-0.0101	Trinidad and Tobago	0.0601
Czech Republic	-0.1200	Mauritius	0.0499	Tunisia	-0.0402
Denmark	-0.0626***	Mexico	-0.0650*	Turkey	-0.0126
Djibouti	0.4690***	Moldova	0.2730	Turkmenistan	0.6270**
Dominican Republic	-0.0059	Mongolia	0.3470**	Uganda	0.1250
Ecuador	-0.0078	Montenegro	0.1510	Ukraine	0.5570
Egypt	-0.0479	Morocco	-0.0133	United Arab Emirates	0.0007
El Salvador	0.0722	Mozambique	0.2710*	United Kingdom	-0.0327
Equatorial Guinea	0.0511	Myanmar	0.2030***	United States	-0.0508**
Eritrea	-0.5020	Namibia	0.2170***	Uruguay	0.0775
Estonia	-0.4300	Nepal	0.0636***	US Virgin Islands	0.3320
Ethiopia	0.3840***	Netherlands	-0.0701***	Uzbekistan	0.5720***
Fiji	-0.0185	New Caledonia	-0.1580	Vanuatu	-0.1070
Finland	-0.0664	New Zealand	-0.0060	Venezuela	-0.0023
France	-0.0840***	Nicaragua	0.0222	Vietnam	-0.0089
French Polynesia	-0.0159	Niger	0.0464	Yemen	-0.1610*
Gabon	-0.1380	Nigeria	0.0510	Zambia	0.0916**
Gambia	-0.0491	Norway	-0.0679***	Zimbabwe	-0.0628

Notes: Table reports OLS estimates of the coefficients based on the following country-specific regressions $\Delta y_{it} = a_i + \varphi_i \Delta y_{i,t-1} + \gamma_i t$. Asterisks indicate statistical significance at the 1% (***), 5% (**) and 10% (*).

Table A.2: Effects of Temperatures and Precipitations on per Capita Real GDP Growth: Variations of Burke et al. (2015) Specifications

	(1) FE+TE +LT+QT	(2) FE +LT+QT	(3) FE+TE	(4) FE
α	0.0127***	0.0102***	0.0083**	0.0093**
	(0.0037)	(0.0038)	(0.0040)	(0.0045)
β	-0.0005***	-0.0004***	-0.0003**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	166	166	166	166
$\max T$	50	50	50	50
avg$T$	39.66	39.66	39.66	39.66
$\min T$	8	8	8	8
$N \times T$	6584	6584	6584	6584

Notes: Column (1) uses the fixed effects (FE), time effects (TE), country-specific linear time trends (LT) and quadratic time trends (QT). Column (2) uses the FE, LT and QT. Column (3) uses the FE and TE. Column (4) uses only the FE. The standard errors are clustered at the country level. Asterisks indicate statistical significance at the 1% (***), 5% (**) and 10% (*).

ification, namely ΔT_{it} and the interaction term, $T_{it} \times \Delta T_{it}$, to allow for weather effects across climates:

$$\Delta y_{it} = a_i + \delta_t + \lambda \Delta T_{it} + \psi T_{it} \times \Delta T_{it} + \alpha T_{it} + \beta T_{it}^2 + \gamma_i t + \phi_i t^2 + \varepsilon_{it}, \tag{A.30}$$

Once again, substituting T_{it} from (A.22) in the above and taking expectations, we have

$$E\left(\Delta y_{it}\right) = c_i + E\left(\delta_t\right) + \left[\gamma_i + \alpha b_{Ti} + \psi b_{Ti}^2 + 2\beta b_{Ti} a_{Ti}\right] t + \left(\beta b_{Ti}^2 + \phi_i\right) t^2$$

where $c_i = a_i + \lambda b_{Ti} + \alpha a_{Ti} + \psi a_{Ti} b_{Ti} + \beta\left(a_{Ti}^2 + \sigma_{Ti}^2\right)$. As before, to ensure a trend-free $E\left(\Delta y_{it}\right)$, one possibility would be to set $E(\delta_t) = 0$ and impose the following restrictions

$$\gamma_i + \alpha b_{Ti} + \psi b_{Ti}^2 + 2\beta b_{Ti} a_{Ti} = 0, \text{ and } \beta b_{Ti}^2 + \phi_i = 0, \text{ for all } i.$$

Other related restrictions can be obtained depending on what is assumed about $E\left(\delta_t\right)$. In effect, KW's generalization of BHM's specification does not resolve the trend problem that surrounds the output growth specifications used in the literature.

Our specification: We consider the following panel ARDL model

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}+1} \psi_\ell \tilde{T}_{it-\ell}(m) + \varepsilon_{it}, \tag{A.31}$$

where y_{it} is the log of real GDP per capita of country i in year t, a_i is the country-specific fixed effect, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T_{i,t-1}^*(m)\right]$ is a measure of temperature relative to its historical norm per annum, T_{it} is the population-weighted average temperature of country i in year t, and $T_{i,t-1}^*(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ is the time-varying historical norm of temperature relative to the preceding m years. We set $m = 30$ in the baseline, given that climate norms are typically formed using 30-year moving averages, but we also check the robustness of our results using $m = 20$ and 40. We also allow for heterogeneous slopes and consider augmenting the panel ARDL model with global and regional output growth to allow for common latent effects.

The above specification has a number of distinct features that differ from the literature and are worth highlighting.

Feature #1. Our specification differs from BHM in modeling a subtle form of nonlinearity at the country level (e.g., by focusing on deviations of T_{it} from country-specific and time-varying norms) and from DJO in using $\tilde{T}_{it}(m)$ in lieu of T_{it}. This modeling choice is supported by Mendelsohn (2016) who argues that researchers should focus on the deviation of T_{it} from its mean, $T^{*}_{i,t-1}(m)$, to estimate unbiased weather effects in panel data studies. Such a transformation also introduces an interaction between weather and climate, and an implicit model of adaptation (see Tol (2021) for details).

To show the benefits of this variable transformation formally, let's take

$$\begin{aligned}
\tilde{T}_{it-\ell}(m) &= \left(\frac{2}{m+1}\right)\left[T_{it-\ell} - T^{*}_{i,t-\ell}(m)\right] \\
&= \left(\frac{2}{m+1}\right)\left(T_{it} - m^{-1}\sum_{s=1}^{m} T_{i,t-s-\ell}\right)
\end{aligned}$$

and use $T_{it} = a_{Ti} + b_{Ti}t + v_{Ti,t}$. We then have

$$\begin{aligned}
\tilde{T}_{it-\ell}(m) &= a_{Ti} + b_{Ti}(t-\ell) + v_{Ti,t-\ell} - m^{-1}\sum_{s=1}^{m}\left[a_{Ti} + b_{Ti}(t-s-\ell) + v_{Ti,t-s-\ell}\right] \\
&= v_{Ti,t-\ell} - m^{-1}\sum_{s=1}^{m} v_{Ti,t-s-\ell},
\end{aligned}$$

and it readily follows that $E\left[\tilde{T}_{it-\ell}(m)\right] = b_{Ti}$. Hence taking expectations of (A.31), it follows that

$$E(\Delta y_{it}) = a_i + \sum_{\ell=1}^{p_y}\varphi_\ell E(\Delta y_{i,t-\ell}) + \left(\sum_{\ell=0}^{p_{\tilde{T}}+1}\psi_\ell\right) b_{Ti},$$

which yields the following time-invariant long-term growth effects from temperature increases

$$E(\Delta y_{it}) = \frac{a_i + \left(\sum_{\ell=0}^{p_{\tilde{T}}+1}\psi_\ell\right) b_{Ti}}{1 - \sum_{\ell=1}^{p}\varphi_\ell}.$$

Therefore, our ARDL specification with $\tilde{T}_{it}(m)$ instead of T_{it}, results in stationary mean growth rates without imposing additional restrictions on b_{Ti} across countries. Also, under growth convergence $a_i + \left(\sum_{\ell=0}^{p_{\tilde{T}}+1}\psi_\ell\right) b_{Ti} = a_j + \left(\sum_{\ell=0}^{p_{\tilde{T}}+1}\psi_\ell\right) b_{Tj}$, countries with a larger trend temperature rise (larger b_{Ti}) must have a higher level of intrinsic (technology induced) output growth to compensate for the larger negative impact from global warming (assuming $\sum_{\ell=0}^{p_{\tilde{T}}+1}\psi_\ell < 0$). In the absence of such compensating effects, we might end up with more divergent growth paths across countries with global warming.

Feature #2. To distinguish between level and growth effects, we re-write equation (A.31) as:

$$\Delta y_{it} = a_i + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \left(\sum_{\ell=0}^{p_{\tilde{T}}} \psi_\ell \right) \tilde{T}_{it-1}(m) + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_\ell \Delta \tilde{T}_{it-\ell}(m) + \varepsilon_{it}, \tag{A.32}$$

If temperature shocks, $\tilde{T}_{it-\ell}(m)$, were to have long-term growth effects, the coefficient of $\tilde{T}_{it-1}(m)$ in the above equation, namely$\sum_{\ell=0}^{p_{\tilde{T}}+1} \psi_\ell$, must be non-zero. The ARDL specification we use is sufficiently flexible and allows us to test this restriction.

In our empirical investigation, we also estimate (A.32) using the absolute value of $\tilde{T}_{it}(m)$, namely $\left|\tilde{T}_{it}(m)\right|$, which has the added advantage of accounting for climate variability as discussed in the main part of the paper. One could also allow for asymmetry in the effects of $\tilde{T}_{it}(m)$ on growth by estimating

$$\begin{aligned} \Delta y_{it} \quad = \quad & a_i + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \left(\sum_{\ell=0}^{p_{\tilde{T}}} \psi_\ell^+ \right) \tilde{T}_{it-1}^+(m) + \left(\sum_{\ell=0}^{p_{\tilde{T}}} \psi_\ell^- \right) \tilde{T}_{it-1}^-(m) \\ & + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{1\ell}^+ \Delta \tilde{T}_{it-\ell}^+(m) + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{1\ell}^- \Delta \tilde{T}_{it-\ell}^-(m) + \varepsilon_{it}, \end{aligned} \tag{A.33}$$

where

$$\tilde{T}_{it}^+(m) = \tilde{T}_{it}(m) I\left[\tilde{T}_{it-\ell}(m) \geq 0\right] \text{ and } \tilde{T}_{it}^-(m) = -\tilde{T}_{it}(m) I\left[\tilde{T}_{it-\ell}(m) < 0\right]$$

The same logic applies in distinguishing between level and growth effects when using $\left|\tilde{T}_{it}(m)\right|$ or estimating the asymmetric effects in equation (A.33). The estimation results are reported in Table A.3 for different values of m. None of the estimated coefficients on $\tilde{T}_{it-1}(m)$, $\left|\tilde{T}_{it-1}(m)\right|$, $\tilde{T}_{it-1}^+(m)$, and $\tilde{T}_{it-1}^-(m)$ are statistically significant at 10% level regardless of m. This finding suggests that temperature shocks, $\tilde{T}_{it-\ell}(m)$ are more likely to affect the level of GDP—a result that is consistent with the microeconomic evidence (see Auffhammer (2018) and Newell et al. (2021) for details) and the growth model developed in this paper. This result is consistent with DJO as they report growth effects of lagged temperature for poor countries only. Moreover, the sign reversal on temperature lags in DJO is indicative of level effects. When BHM estimate their distributed lag models with 1–5 lags of the quadratic temperature polynomial, they find that cumulative temperature effects on growth is not statistically distinguishable from zero. Moreover, as in DJO, lagged temperature effects exhibit sign reversals (see Newell et al. (2021) for details). Thus, we drop $\tilde{T}_{it-1}(m)$, $\left|\tilde{T}_{it-1}(m)\right|$, $\tilde{T}_{it-1}^+(m)$, and $\tilde{T}_{it-1}^-(m)$ from all regressions in the main text. Note that there could be long-term growth effects if temperature keeps rising above its country-specific time-varying norms owing to climate change, $\left(\sum_{\ell=0}^{p_{\tilde{T}}} \psi_\ell\right) \neq 0$ and $\sum_{\ell=0}^{p_{\tilde{T}}} \beta_\ell \neq 0$ in equation (A.32).[19]

Feature #3. To test the impact of weather shocks across climates, we consider a heterogenous panel data model where the coefficients of lagged output growth and temperature variables are

[19] As an example, while the stock of capital will determine the level of GDP, capital accumulation affects GDP growth.

Table A.3: Level Effects? Long-Run Impact of Temperature Shocks on per Capita Real GDP Growth, 1960–2014

Historical Norm:	$m = 20$		$m = 30$		$m = 40$	
	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE
(a) Specification 1						
$\tilde{T}_{it-1}(m)$	-0.0176	0.0011	-0.0270	0.0016	-0.0360	0.0281
	(0.0302)	(0.0416)	(0.0397)	(0.0587)	(0.0478)	(0.0718)
(b) Specification 2						
$\left\lvert\tilde{T}_{it-1}(m)\right\rvert$	-0.0174	-0.0221	-0.0140	-0.0037	-0.0031	0.0260
	(0.0779)	(0.0843)	(0.1085)	(0.1249)	(0.1316)	(0.1543)
(c) Specification 3						
$\tilde{T}^{+}_{it-1}(m)$	-0.0212	-0.0057	-0.0106	0.0370	0.0068	0.1023
	(0.0780)	(0.0861)	(0.1093)	(0.1240)	(0.1333)	(0.1526)
$\tilde{T}^{-}_{it-1}(m)$	0.0185	0.0222	0.0575	0.1410	0.1132	0.2930
	(0.1006)	(0.0996)	(0.1425)	(0.1503)	(0.1792)	(0.1939)
$N \times T$	6714	6674	6714	6674	6714	6674

Notes: Specification 1 is given by $\Delta y_{it} = a_i + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \left(\sum_{\ell=0}^{p_{\tilde{T}}} \psi_\ell\right) \tilde{T}_{it-1}(m) + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_\ell \Delta \tilde{T}_{it-\ell}(m) + \varepsilon_{it}$, where y_{it} is the log of real GDP per capita of country i in year t, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^{*}_{i,t-1}(m)\right]$ is a measure of temperature relative to its historical norm per annum, T_{it} is the population-weighted average temperature of country i in year t, and $T^{*}_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ is the time-varying historical norm of temperature over the preceding m years in each t. Specification 2 estimates the same model with $\left\lvert\tilde{T}_{it}(m)\right\rvert$ and specification 3 allows for asymmetry in the effects of $\tilde{T}_{it}(m)$ on growth by using $\tilde{T}^{+}_{it}(m) = \tilde{T}_{it}(m) I\left[\tilde{T}_{it-\ell}(m) \geq 0\right]$ and $\tilde{T}^{-}_{it}(m) = -\tilde{T}_{it}(m) I\left[\tilde{T}_{it-\ell}(m) < 0\right]$ in regressions. Columns labelled (a) report the FE estimates and columns labelled (b) report the half-panel jackknife FE (HPJ-FE) estimates, which corrects the bias in columns (a). The standard errors are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

allowed to vary across countries, and report the mean group (MG) estimates of marginal weather effects for different regions (e.g., hot and cold). We believe this is an improvement over Kalkuhl and Wenz (2020), who allow for heterogeneity by using interaction terms such as $\tilde{T}_{it}(m) \times \bar{T}_i$ where $\bar{T}_i$ measures the average temperature in country i over 1960–2014.

Feature #4. We exclude time effects or time trends from most regressions in this paper as they could result in overfitting and worse out-of-sample predictions. The inferior statistical performance of models with trends is also confirmed by model cross-validation of Newell et al. (2021). To treat unobserved factors, instead we augment the ARDL panel regressions with lagged world output growth (regional output growth could also be used), and estimated the following augmented ARDL specification:

$$\Delta y_{it} = a_i + \omega \Delta \bar{y}_{w,t-1} + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}} \beta \Delta \left| \tilde{T}_{it-\ell}(m) \right| + \varepsilon_{it},$$

where $\bar{y}_{wt}$ is the log of world's real GDP per capita in year t (capturing common time effects). The results are reported in Table A.4.

A.3 Climate Change: Historical Patterns

This appendix examines how global temperature has evolved over the past half century (1960–2014) as well as over a longer period (1900–2014). Allowing for the significant heterogeneity that exists across countries with respect to changes in temperature over time, we estimate country-specific regressions

$$T_{it} = a_{Ti} + b_{Ti}t + v_{Ti,t}, \text{ for } i = 1, 2, ..., N = 174, \tag{A.34}$$

where T_{it} denotes the population-weighted average temperature of country i at year t. The per annum average increase in land temperature for country i is given by b_{Ti}, with the corresponding global measure defined by $b_T = N^{-1}\Sigma_{i=1}^{N} b_{Ti}$. Individual country estimates of b_{Ti} together with their standard errors are summarized in Table A.5. The estimates range from -0.0044 (Samoa) to 0.0390 (Afghanistan). For 169 countries (97.1% of cases), these estimates are positive; out of which, the estimates in 161 countries (95.3% of cases) are statistically significant at the 5% level. There are only five countries for which the estimate, $\widehat{b}_{Ti}$, is not positive: Bangladesh, Bolivia, Cuba, Ecuador and Samoa, but none of them are statistically significant at the 5% level. See also Figure A.2 which illustrates the increase in temperature per year for the 174 countries over 1960–2014.

Table A.6 presents estimates of b_{Ti} over a longer time horizon (1900–2014). The country-specific estimates of b_{Ti} for the 174 countries over this longer sample period range from -0.0008 (Greece) to 0.0190 (Haiti). In 172 countries (98.9% of the cases) these estimates are positive and in 156 countries (90.7% of cases) they are statistically significant at the 5% level. There are only two countries for which the estimate of b_{Ti} is not positive: Greece and Macedonia but these are not statistically significant. The estimated results over 1900–2014 echo those obtained over the 1960–2014 period. Temperature has been rising for pretty much all of the countries in our sample, indicating that T_{it} is trended. As discussed in the main text, the econometric specifications in the

Table A.4: Long-Run Effects of Climate Change on per Capita Real GDP Growth, 1960–2014 (Using Absolute Value of Deviations of Climate Variables from their Historical Norm)

	Specification 1						Specification 2					
	$m=20$		$m=30$		$m=40$		$m=20$		$m=30$		$m=40$	
	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE	(a) FE	(b) HPJ-FE
$\widehat{\theta}_{\Delta\|\tilde{T}_{it}(m)\|}$	-0.313**	-0.456**	-0.494**	-0.728***	-0.602**	-0.859**	-0.317**	-0.461**	-0.495**	-0.733***	-0.605**	-0.873**
	(0.141)	(0.191)	(0.197)	(0.270)	(0.248)	(0.344)	(0.140)	(0.191)	(0.197)	(0.270)	(0.249)	(0.344)
$\widehat{\theta}_{\Delta\|\tilde{P}_{it}(m)\|}$	-0.0653	-0.109	-0.0015	-0.0845	-0.198	-0.333	-	-	-	-	-	-
	(0.233)	(0.323)	(0.466)	(0.508)	(0.635)	(0.684)	-	-	-	-	-	-
$\widehat{\phi}$	0.690***	0.625***	0.690***	0.625***	0.690***	0.626***	0.691***	0.625***	0.691***	0.625***	0.691***	0.625***
	(0.0506)	(0.0452)	(0.506)	(0.0453)	(0.0182)	(0.0453)	(0.0506)	(0.0453)	(0.0505)	(0.0453)	(0.0182)	(0.0453)
ω	0.312***	0.313***	0.307***	0.302***	0.310***	0.307***	0.312***	0.311***	0.308***	0.304***	0.309***	0.304***
	(0.0413)	(0.0532)	(0.0414)	(0.0534)	(0.0413)	(0.0533)	(0.0413)	(0.0532)	(0.0413)	(0.0532)	(0.0414)	(0.0535)
N	174	174	174	174	174	174	174	174	174	174	174	174
$\max T$	50	50	50	50	50	50	50	50	50	50	50	50
avg$T$	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36	38.36
$\min T$	2	2	2	2	2	2	2	2	2	2	2	2
$N \times T$	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674	6714	6674

Notes: Specification 1 is given by $\Delta y_{it} = a_i + \omega \Delta \bar{y}_{w,t-1} + \sum_{\ell=1}^{p_y} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{1\ell} \left| \tilde{T}_{it-\ell}(m) \right| + \sum_{\ell=0}^{p_{\tilde{T}}} \beta_{2\ell} \left| \tilde{P}_{it-\ell}(m) \right| + \varepsilon_{it}$, where y_{it} is the log of real GDP per capita of country i in year t, $\bar{y}_{wt}$ is the log of world's real GDP per capita in year t, $\tilde{T}_{it}(m) = \left(\frac{2}{m+1}\right)\left[T_{it} - T^*_{i,t-1}(m)\right]$ and $\tilde{P}_{it}(m) = \left(\frac{2}{m+1}\right)\left[P_{it} - P^*_{i,t-1}(m)\right]$ are measures of temperature and precipitation relative to their historical norms per annum, T_{it} and P_{it} are the population-weighted average temperature and of precipitation country i in year t, and $T^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} T_{i,t-\ell}$ and $P^*_{i,t-1}(m) = \frac{1}{m}\sum_{\ell=1}^{m} P_{i,t-\ell}$ are the time-varying historical norms of temperature and precipitation over the preceding m years in each t. The long-run effects, θ_i, are calculated from the OLS estimates of the short-run coefficients in equation (1): $\theta_1 = \phi^{-1}\sum_{\ell=0}^{p} \beta_{1\ell}$ and $\theta_2 = \phi^{-1}\sum_{\ell=0}^{p} \beta_{2\ell}$, where $\phi = 1 - \sum_{\ell=1}^{p} \varphi_\ell$. Specification 2 drops the precipitation variables from the baseline model. The standard errors are estimated by the estimator proposed in Proposition 4 of Chudik et al. (2018). Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A.5: Individual Country Estimates of the Average Yearly Rise in Temperature Over the Period 1960–2014

Country	$\widehat{b}_{Ti}$	Country	$\widehat{b}_{Ti}$	Country	$\widehat{b}_{Ti}$
Afghanistan	0.0390***	Georgia	0.0159***	Oman	0.0082***
Albania	0.0240***	Germany	0.0229***	Pakistan	0.0096***
Algeria	0.0288***	Ghana	0.0184***	Panama	0.0169***
Angola	0.0193***	Greece	0.0112***	Papua New Guinea	0.0074***
Argentina	0.0070***	Greenland	0.0381***	Paraguay	0.0047
Armenia	0.0140**	Guatemala	0.0276***	Peru	0.0065**
Australia	0.0094***	Guinea	0.0166***	Philippines	0.0068***
Austria	0.0170***	Guinea-Bissau	0.0237***	Poland	0.0255***
Azerbaijan	0.0188***	Guyana	0.0029	Portugal	0.0104***
Bahamas	0.0195***	Haiti	0.0163***	Puerto Rico	0.0059**
Bangladesh	-0.0007	Honduras	0.0207***	Qatar	0.0271***
Belarus	0.0316***	Hungary	0.0163***	Romania	0.0186***
Belgium	0.0261***	Iceland	0.0206***	Russian Federation	0.0348***
Belize	0.0114***	India	0.0095***	Rwanda	0.0158***
Benin	0.0180***	Indonesia	0.0053***	Saint Vincent and the Grenadines	0.0124***
Bhutan	0.0143***	Iran	0.0229***	Samoa	-0.0044*
Bolivia	-0.0000	Iraq	0.0244***	Sao Tome and Principe	0.0240***
Bosnia and Herzegovina	0.0373***	Ireland	0.0151***	Saudi Arabia	0.0207***
Botswana	0.0260***	Israel	0.0168***	Senegal	0.0255***
Brazil	0.0162***	Italy	0.0283***	Serbia	0.0155***
Brunei Darussalam	0.0096***	Jamaica	0.0204***	Sierra Leone	0.0161***
Bulgaria	0.0124***	Japan	0.0133***	Slovakia	0.0197***
Burkina Faso	0.0191***	Jordan	0.0146***	Slovenia	0.0298***
Burundi	0.0186***	Kazakhstan	0.0240***	Solomon Islands	0.0096***
Cabo Verde	0.0181***	Kenya	0.0176***	Somalia	0.0213***
Cambodia	0.0167***	Kuwait	0.0254***	South Africa	0.0073***
Cameroon	0.0117***	Kyrgyzstan	0.0280***	South Korea	0.0081*
Canada	0.0300***	Laos	0.0091***	South Sudan	0.0308***
Central African Republic	0.0099***	Latvia	0.0304***	Spain	0.0260***
Chad	0.0181***	Lebanon	0.0247***	Sri Lanka	0.0107***
Chile	0.0102***	Lesotho	0.0099**	Sudan	0.0295***
China	0.0230***	Liberia	0.0094***	Suriname	0.0042
Colombia	0.0061**	Libya	0.0333***	Swaziland	0.0174***
Comoros	0.0062*	Lithuania	0.0277***	Sweden	0.0210***
Congo	0.0146***	Luxembourg	0.0281***	Switzerland	0.0183***
Congo DRC	0.0150***	Macedonia	0.0129***	Syria	0.0225***
Costa Rica	0.0173***	Madagascar	0.0214***	Tajikistan	0.0002
Côte d'Ivoire	0.0131***	Malawi	0.0234***	Tanzania	0.0104***
Croatia	0.0247***	Malaysia	0.0133***	Thailand	0.0055**
Cuba	-0.0006	Mali	0.0214***	Togo	0.0185***
Cyprus	0.0151***	Mauritania	0.0243***	Trinidad and Tobago	0.0243***
Czech Republic	0.0192***	Mauritius	0.0216***	Tunisia	0.0368***
Denmark	0.0195***	Mexico	0.0117***	Turkey	0.0141**
Djibouti	0.0135***	Moldova	0.0202***	Turkmenistan	0.0255***
Dominican Republic	0.0152***	Mongolia	0.0276***	Uganda	0.0198***
Ecuador	-0.0031	Montenegro	0.0196***	Ukraine	0.0263***
Egypt	0.0272***	Morocco	0.0211***	United Arab Emirates	0.0158***
El Salvador	0.0319***	Mozambique	0.0148***	United Kingdom	0.0129***
Equatorial Guinea	0.0275***	Myanmar	0.0200***	United States	0.0147***
Eritrea	0.0178***	Namibia	0.0262***	Uruguay	0.0151***
Estonia	0.0330***	Nepal	0.0176***	US Virgin Islands	0.0226***
Ethiopia	0.0219***	Netherlands	0.0240***	Uzbekistan	0.0214***
Fiji	0.0115***	New Caledonia	0.0118***	Vanuatu	0.0279***
Finland	0.0304***	New Zealand	0.0018	Venezuela	0.0160***
France	0.0215***	Nicaragua	0.0286***	Vietnam	0.0054**
French Polynesia	0.0236***	Niger	0.0075	Yemen	0.0345***
Gabon	0.0177***	Nigeria	0.0163***	Zambia	0.0190***
Gambia	0.0234***	Norway	0.0232***	Zimbabwe	0.0139***

Notes: $\widehat{b}_{Ti}$ is the OLS estimate of b_{Ti} in the country-specific regressions $T_{it} = a_{Ti} + b_{Ti}t + v_{T,it}$, where T_{it} denotes the population-weighted average temperature (°C). Asterisks indicate statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

Table A.6: Individual Country Estimates of the Average Yearly Rise in Temperature Over the Period 1900–2014

Country	$\widehat{b}_{Ti}$	Country	$\widehat{b}_{Ti}$	Country	$\widehat{b}_{Ti}$
Afghanistan	0.0136***	Georgia	0.0044**	Oman	0.0047***
Albania	0.0036**	Germany	0.0063***	Pakistan	0.0043***
Algeria	0.0067***	Ghana	0.0035***	Panama	0.0060***
Angola	0.0099***	Greece	-0.0008	Papua New Guinea	0.0026**
Argentina	0.0038***	Greenland	0.0110***	Paraguay	0.0032**
Armenia	0.0056**	Guatemala	0.0065***	Peru	0.0039***
Australia	0.0041***	Guinea	0.0028***	Philippines	0.0048***
Austria	0.0056***	Guinea-Bissau	0.0051***	Poland	0.0063***
Azerbaijan	0.0064***	Guyana	0.0051***	Portugal	0.0051***
Bahamas	0.0048***	Haiti	0.0190***	Puerto Rico	0.0023***
Bangladesh	0.0033***	Honduras	0.0086***	Qatar	0.0125***
Belarus	0.0094***	Hungary	0.0033*	Romania	0.0043**
Belgium	0.0057***	Iceland	0.0034*	Russian Federation	0.0111***
Belize	0.0041***	India	0.0029***	Rwanda	0.0050***
Benin	0.0032***	Indonesia	0.0025***	Saint Vincent and the Grenadines	0.0050***
Bhutan	0.0055***	Iran	0.0072***	Samoa	0.0050***
Bolivia	0.0011	Iraq	0.0083***	Sao Tome and Principe	0.0071***
Bosnia and Herzegovina	0.0106***	Ireland	0.0057***	Saudi Arabia	0.0070***
Botswana	0.0098***	Israel	0.0047***	Senegal	0.0074***
Brazil	0.0061***	Italy	0.0045***	Serbia	0.0038**
Brunei Darussalam	0.0002	Jamaica	0.0134***	Sierra Leone	0.0031***
Bulgaria	0.0012	Japan	0.0099***	Slovakia	0.0061***
Burkina Faso	0.0045***	Jordan	0.0032*	Slovenia	0.0062***
Burundi	0.0075***	Kazakhstan	0.0122***	Solomon Islands	0.0020**
Cabo Verde	0.0039***	Kenya	0.0026***	Somalia	0.0071***
Cambodia	0.0045***	Kuwait	0.0091***	South Africa	0.0051***
Cameroon	0.0039***	Kyrgyzstan	0.0146***	South Korea	0.0101***
Canada	0.0110***	Laos	0.0028***	South Sudan	0.0102***
Central African Republic	0.0020**	Latvia	0.0094***	Spain	0.0080***
Chad	0.0048***	Lebanon	0.0030*	Sri Lanka	0.0050***
Chile	0.0017**	Lesotho	0.0026**	Sudan	0.0102***
China	0.0064***	Liberia	0.0018**	Suriname	0.0012
Colombia	0.0098***	Libya	0.0076***	Swaziland	0.0103***
Comoros	0.0053***	Lithuania	0.0080***	Sweden	0.0064**
Congo	0.0064***	Luxembourg	0.0050***	Switzerland	0.0046***
Congo DRC	0.0051***	Macedonia	-0.0000	Syria	0.0055***
Costa Rica	0.0031*	Madagascar	0.0018*	Tajikistan	0.0099***
Côte d'Ivoire	0.0013	Malawi	0.0162***	Tanzania	0.0026***
Croatia	0.0039**	Malaysia	0.0014*	Thailand	0.0012
Cuba	0.0021***	Mali	0.0057***	Togo	0.0023**
Cyprus	0.0080***	Mauritania	0.0083***	Trinidad and Tobago	0.0035**
Czech Republic	0.0040**	Mauritius	0.0053***	Tunisia	0.0087***
Denmark	0.0044**	Mexico	0.0060***	Turkey	0.0045**
Djibouti	0.0057***	Moldova	0.0089***	Turkmenistan	0.0092***
Dominican Republic	0.0111***	Mongolia	0.0111***	Uganda	0.0048***
Ecuador	0.0091***	Montenegro	0.0070***	Ukraine	0.0089***
Egypt	0.0056***	Morocco	0.0041***	United Arab Emirates	0.0055***
El Salvador	0.0050**	Mozambique	0.0134***	United Kingdom	0.0038***
Equatorial Guinea	0.0093***	Myanmar	0.0051***	United States	0.0036***
Eritrea	0.0046***	Namibia	0.0093***	Uruguay	0.0064***
Estonia	0.0093***	Nepal	0.0039***	US Virgin Islands	0.0069***
Ethiopia	0.0049***	Netherlands	0.0043**	Uzbekistan	0.0096***
Fiji	0.0045***	New Caledonia	0.0006	Vanuatu	0.0043***
Finland	0.0070**	New Zealand	0.0043***	Venezuela	0.0152***
France	0.0069***	Nicaragua	0.0086***	Vietnam	0.0015*
French Polynesia	0.0062***	Niger	0.0009	Yemen	0.0154***
Gabon	0.0074***	Nigeria	0.0044***	Zambia	0.0033**
Gambia	0.0046***	Norway	0.0054**	Zimbabwe	0.0066***

Notes: $\widehat{b}_{Ti}$ is the OLS estimate of b_{Ti} in the country-specific regressions $T_{it} = a_{Ti} + b_{Ti}t + v_{T,it}$, where T_{it} denotes the population-weighted average temperature (°C). Asterisks indicate statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

literature involve real GDP growth rates and the level of temperature, T_{it}, and in some cases also T_{it}^2; see, for instance, Dell et al. (2012) and Burke et al. (2015). But in cases where T_{it} is trended, which is the situation in almost all the countries in the world (based on both the 1900–2014 and the 1960–2014 samples), inclusion of T_{it} in the regressions will induce a quadratic trend in equilibrium log per capita output (or equivalently a linear trend in per capita output growth) which is not desirable and can bias the estimates of the growth-climate change equation.

The above country-specific estimates are also in line with the average increases in global temperature published by the *Goddard Institute for Space Studies* (GISS) at National Aeronautics and Space Administration (NASA), and close to the estimates by the *National Centers for Environmental Information* (NCEI) at the National Oceanic and Atmospheric Administration (NOAA). The right panel in Figure A.1 plots the global land temperatures between 1960 and 2014 recorded by NOAA and NASA; clearly showing that T_t is trended. IPCC (2013) also estimates similar trends using various datasets and over different sub-periods. For instance, the trend estimates of global land-surface air temperature (in °C per decade) over the 1951-2012 period, based on data from the Climatic Research Unit's *CRUTEM4.1.1.0*, NOAA's *Global Historical Climatology Network Version 3* (GHCNv3), and *Berkeley Earth*, are reported as 0.175 (±0.037), 0.197 (±0.031), and 0.175 (±0.029), respectively with 90% confidence intervals in brackets; see Chapter 2 of IPCC (2013).

Using the individual country estimates in Table A.5, the average rise in global temperature over the 1960-2014 period is given by $\hat{b}_{\mathcal{T}} = 0.0181(0.0007)$ degrees Celsius per annum, which is statistically highly significant.[20] In comparison, according to NASA observations global land temperature has risen by 0.89°C between 1960 and 2014, or around 0.0165°C per year, and based on NCEI data the global land-surface air temperature has risen by 1.07°C over the same period, or around $0.0198°C$ per year. Thus our global estimate of $0.0181°C$ lies in the middle of these two estimates, but has the added advantage of having a small standard error, noting that it is a pooled estimate across a large number of countries.

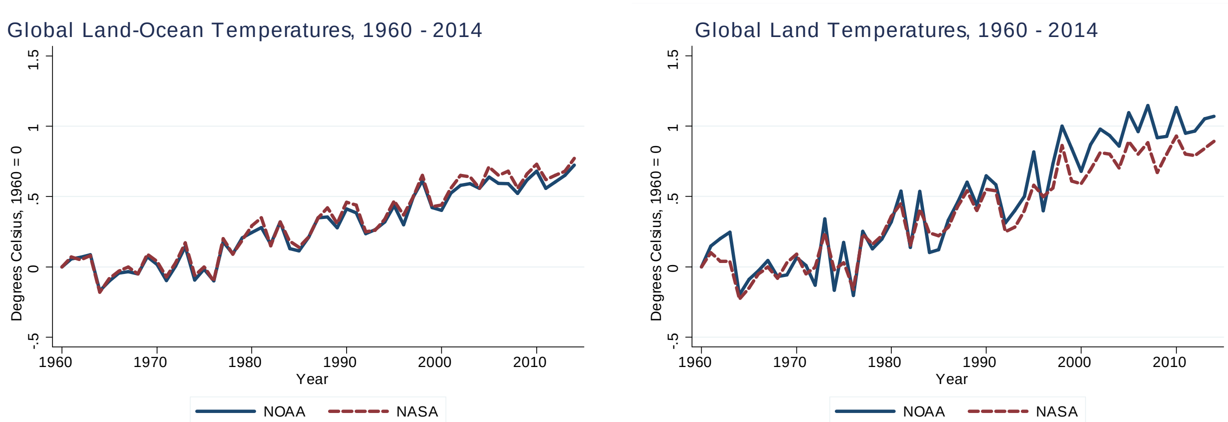
We also plot the global land-surface air and sea-surface water temperatures in the left panel of Figure A.1. We observe an upward trend using data from NOAA (a rise of 0.72°C) or data from NASA (a rise of 0.77°C) between 1960 and 2014; equivalent to 0.0134°C and 0.0143°C per year, respectively. Note that the land-surface air temperature has risen by more than the sea-surface water temperature over this period, because oceans have a larger effective heat capacity and lose more heat through evaporation.

A.4 Additional Results

We reported the real GDP per capita losses arising from global warming under the RCP 2.6 and RCP 8.5 scenarios, compared to the reference case, in country heat maps and for the year 2100 only in the main text. In Table A.7 we make available all of the 174 country-specific estimates over various horizons (by year 2030, 2050, and 2100).

[20] The standard error of $\hat{b}_{\mathcal{T}} = N^{-1}\Sigma_{i=1}^{N}\hat{b}_{\mathcal{T}i}$, given in round brackets, is computed using the mean group approach of Pesaran and Smith (1995).

Figure A.1: Global Land-Surface Air and Sea-Surface Water Temperatures (Degrees Celsius, 1960 = 0)



Note: The left panel shows the global land-surface air and sea-surface water temperatures, and the right panel shows the global land-surface air temperatures, both over the 1960–2014 period. The blue lines show the temperatures observed by the *National Centers for Environmental Information* (NCEI) at the National Oceanic and Atmospheric Administration (NOAA); and the broken red lines show the temperatures observed by the *Goddard Institute for Space Studies* (GISS) at National Aeronautics and Space Administration (NASA). The temperatures in 1960 are standardised to zero.

Figure A.2: Temperature Increase per year for the 174 Countries, 1960–2014

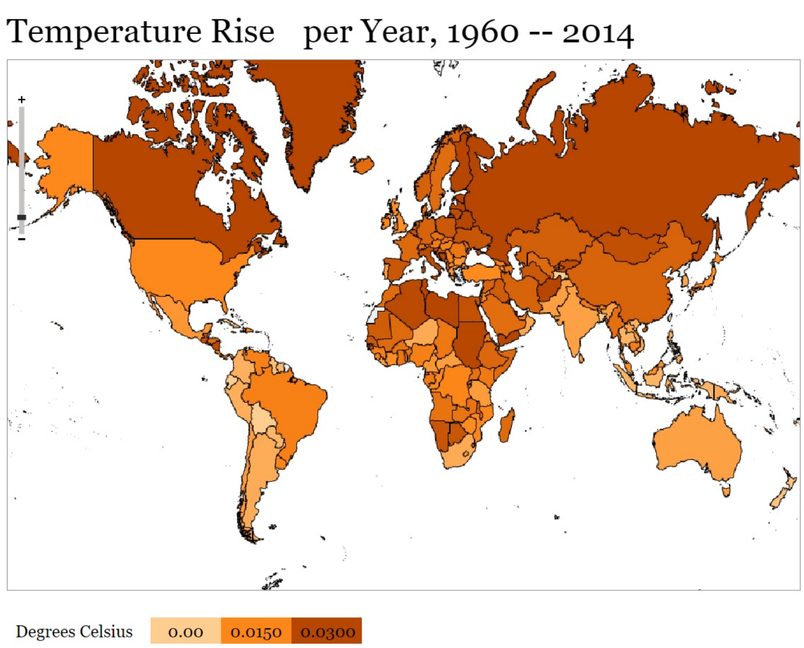


Table A.7: Percent Loss in GDP per capita by 2030, 2050, and 2100 under the RCP 2.6 and RCP 8.5 Scenarios

	Key Variables in Equation (13)					Percent Loss in GDP per capita					
	$\bar{T}i$	$\widehat{b}_{Ti}^{0}$	$\widehat{\sigma}_{Ti}$	d_i		RCP 2.6 Scenario			RCP 8.5 Scenario		
				RCP 2.6	RCP 8.5	2030	2050	2100	2030	2050	2100
Afghanistan	12.35	0.039	0.61	-0.0005	0.0009	-0.35	-0.78	-1.18	0.70	1.96	5.54
Albania	12.94	0.024	0.48	0.0002	0.0014	0.15	0.42	1.22	1.03	3.13	8.86
Algeria	23.02	0.029	0.41	-0.0009	0.0004	-0.59	-0.94	1.33	0.34	0.92	2.56
Angola	21.90	0.019	0.34	-0.0002	0.0009	-0.14	-0.31	-0.52	0.71	2.09	5.84
Argentina	14.14	0.007	0.29	0.0005	0.0013	0.20	0.71	2.50	0.79	2.78	8.17
Armenia	7.82	0.014	0.82	0.0000	0.0012	-0.01	-0.02	-0.05	0.42	1.57	6.03
Australia	21.69	0.009	0.35	0.0002	0.0011	0.06	0.17	0.56	0.64	2.25	6.93
Austria	6.94	0.017	0.54	0.0001	0.0013	0.06	0.16	0.46	0.71	2.39	7.58
Azerbaijan	12.99	0.019	0.65	-0.0008	0.0004	-0.21	-0.23	1.25	0.18	0.54	1.80
Bahamas	25.59	0.020	0.28	-0.0008	-0.0001	-0.50	-0.52	2.34	-0.08	-0.20	-0.44
Bangladesh	25.55	-0.001	0.26	0.0005	0.0014	0.06	0.42	2.15	0.55	2.68	8.59
Belarus	6.21	0.032	0.83	-0.0003	0.0009	-0.12	-0.28	-0.54	0.52	1.58	5.04
Belgium	9.45	0.026	0.64	-0.0005	0.0004	-0.23	-0.47	-0.29	0.25	0.71	2.17
Belize	25.54	0.011	0.27	-0.0001	0.0008	-0.04	-0.09	-0.18	0.55	1.75	5.10
Benin	27.38	0.018	0.25	-0.0003	0.0007	-0.22	-0.48	-0.50	0.59	1.65	4.43
Bhutan	7.84	0.014	0.36	0.0016	0.0026	1.18	3.70	10.33	2.23	6.64	17.76
Bolivia	21.47	0.000	0.33	0.0003	0.0015	0.02	0.15	0.90	0.53	2.64	8.82
Bosnia and Herzegovina	8.96	0.037	0.58	0.0004	0.0015	0.27	0.74	2.07	1.24	3.56	9.75
Botswana	21.96	0.026	0.62	-0.0003	0.0011	-0.13	-0.30	-0.53	0.67	2.07	6.37
Brazil	24.45	0.016	0.24	0.0000	0.0011	0.02	0.06	0.15	0.99	2.79	7.35
Brunei Darussalam	26.84	0.010	0.27	-0.0005	0.0003	-0.15	-0.07	1.41	0.16	0.50	1.65
Bulgaria	9.97	0.012	0.51	0.0009	0.0021	0.39	1.39	4.84	1.24	4.41	13.16
Burkina Faso	28.40	0.019	0.29	-0.0004	0.0007	-0.26	-0.53	-0.26	0.60	1.72	4.71
Burundi	20.28	0.019	0.43	0.0001	0.0012	0.08	0.21	0.59	0.81	2.56	7.46
Cabo Verde	21.02	0.018	0.46	0.0002	0.0009	0.10	0.27	0.80	0.57	1.80	5.54
Cambodia	26.95	0.017	0.29	-0.0007	0.0001	-0.36	-0.38	1.84	0.10	0.26	0.74
Cameroon	24.43	0.012	0.29	-0.0003	0.0006	-0.13	-0.23	0.08	0.39	1.23	3.75
Canada	-6.20	0.030	0.77	0.0004	0.0021	0.20	0.56	1.68	1.37	4.40	13.08
Central African Republic	25.30	0.010	0.32	-0.0001	0.0008	-0.05	-0.11	-0.15	0.49	1.65	5.12
Chad	27.57	0.018	0.46	-0.0009	0.0002	-0.31	-0.18	2.65	0.11	0.31	0.92
Chile	8.16	0.010	0.31	0.0008	0.0017	0.50	1.68	5.18	1.23	3.97	11.08
China	6.68	0.023	0.30	-0.0006	0.0007	-0.45	-0.80	0.45	0.58	1.62	4.35
Colombia	24.65	0.006	0.28	0.0000	0.0010	0.00	-0.01	-0.03	0.52	1.93	6.02
Comoros	25.08	0.006	0.40	0.0004	0.0012	0.11	0.39	1.57	0.49	1.97	6.71
Congo	24.63	0.015	0.25	-0.0002	0.0008	-0.12	-0.27	-0.40	0.62	1.81	4.99
Congo DRC	23.92	0.015	0.26	-0.0001	0.0009	-0.09	-0.22	-0.41	0.73	2.13	5.81
Costa Rica	23.41	0.017	0.35	0.0007	0.0015	0.49	1.47	4.33	1.20	3.64	9.95
Côte d'Ivoire	26.35	0.013	0.27	-0.0003	0.0006	-0.15	-0.29	-0.09	0.45	1.37	3.96
Croatia	11.27	0.025	0.58	-0.0002	0.0009	-0.10	-0.24	-0.46	0.59	1.79	5.52
Cuba	25.39	-0.001	0.28	0.0005	0.0013	0.06	0.44	2.26	0.44	2.28	7.68
Cyprus	18.67	0.015	0.48	-0.0001	0.0009	-0.02	-0.05	-0.12	0.50	1.66	5.37
Czech Republic	7.47	0.019	0.64	-0.0002	0.0009	-0.07	-0.16	-0.28	0.41	1.33	4.52
Denmark	7.90	0.019	0.74	-0.0005	0.0004	-0.13	-0.24	-0.02	0.16	0.49	1.63
Djibouti	28.00	0.013	0.35	-0.0009	0.0001	-0.25	0.17	3.62	0.03	0.08	0.22
Dominican Republic	25.19	0.015	0.37	-0.0002	0.0006	-0.08	-0.18	-0.31	0.35	1.06	3.31
Ecuador	22.32	-0.003	0.39	0.0005	0.0014	0.00	0.19	1.49	0.27	1.94	7.70
Egypt	22.20	0.027	0.44	-0.0004	0.0008	-0.29	-0.61	-0.69	0.63	1.79	5.06
El Salvador	24.59	0.032	0.37	-0.0001	0.0008	-0.05	-0.12	-0.31	0.76	2.08	5.50
Equatorial Guinea	24.32	0.027	0.45	-0.0007	0.0002	-0.40	-0.76	-0.02	0.14	0.36	1.00
Eritrea	25.95	0.018	0.50	-0.0002	0.0009	-0.07	-0.16	-0.29	0.53	1.70	5.42
Estonia	5.22	0.033	0.89	-0.0007	0.0005	-0.27	-0.54	-0.33	0.28	0.80	2.47
Ethiopia	22.58	0.022	0.25	-0.0004	0.0006	-0.30	-0.66	-0.72	0.56	1.52	4.00
Fiji	24.45	0.011	0.27	0.0004	0.0011	0.25	0.77	2.39	0.81	2.54	7.12
Finland	1.47	0.030	0.96	-0.0011	0.0003	-0.35	-0.46	1.48	0.12	0.34	1.02
France	10.55	0.022	0.50	-0.0001	0.0010	-0.03	-0.07	-0.17	0.62	1.92	5.82
French Polynesia	23.83	0.024	0.30	0.0005	0.0011	0.43	1.17	3.16	1.03	2.83	7.43
Gabon	24.44	0.018	0.32	-0.0002	0.0007	-0.10	-0.24	-0.45	0.55	1.61	4.56
Gambia	26.43	0.023	0.32	0.0002	0.0012	0.20	0.53	1.44	1.15	3.20	8.43

Notes: We consider persistent increases in temperatures based on the RCP 2.6 and RCP 8.5 scenarios. The losses are based on $\Delta_{ih}(d_i)$, see equation (13), with $h = 16$, 36, and 86 (corresponding to the year 2030, 2050, and 2100, respectively) and $m = 30$.

Table A.7: Percent Loss in GDP per capita by 2030, 2050, and 2100 under the RCP 2.6 and RCP 8.5 Scenarios (continued)

	Key Variables in Equation (13)					Percent Loss in GDP per capita					
	$\bar{T}i$	$\hat{b}^0_{Ti}$	$\hat{\sigma}_{Ti}$	d_i		RCP 2.6 Scenario			RCP 8.5 Scenario		
				RCP 2.6	RCP 8.5	2030	2050	2100	2030	2050	2100
Georgia	8.73	0.016	0.67	-0.0004	0.0008	-0.09	-0.18	-0.05	0.33	1.12	4.01
Germany	8.47	0.023	0.65	-0.0006	0.0004	-0.22	-0.39	0.08	0.21	0.61	1.92
Ghana	27.14	0.018	0.24	-0.0004	0.0005	-0.31	-0.61	-0.10	0.43	1.18	3.17
Greece	13.82	0.011	0.49	0.0008	0.0019	0.35	1.26	4.45	1.12	4.04	12.21
Greenland	-19.71	0.038	0.73	-0.0008	0.0007	-0.42	-0.85	-0.52	0.49	1.39	4.10
Guatemala	23.56	0.028	0.28	-0.0002	0.0008	-0.16	-0.40	-0.89	0.80	2.12	5.48
Guinea	25.53	0.017	0.25	-0.0002	0.0008	-0.12	-0.28	-0.50	0.71	2.03	5.45
Guinea-Bissau	26.74	0.024	0.28	-0.0002	0.0007	-0.20	-0.47	-0.88	0.70	1.91	5.02
Guyana	25.98	0.003	0.33	0.0003	0.0013	0.07	0.27	1.21	0.56	2.42	7.89
Haiti	24.55	0.016	0.53	0.0001	0.0009	0.04	0.10	0.27	0.45	1.49	4.95
Honduras	25.27	0.021	0.35	-0.0003	0.0006	-0.19	-0.42	-0.57	0.46	1.33	3.78
Hungary	10.33	0.016	0.64	-0.0002	0.0009	-0.07	-0.15	-0.20	0.41	1.41	4.96
Iceland	1.10	0.021	0.65	-0.0007	0.0003	-0.23	-0.32	0.83	0.12	0.33	1.00
India	23.99	0.009	0.25	0.0004	0.0015	0.26	0.81	2.57	1.16	3.62	9.90
Indonesia	25.40	0.005	0.15	0.0003	0.0011	0.19	0.61	1.92	0.91	2.79	7.51
Iran	17.33	0.023	0.52	-0.0001	0.0012	-0.04	-0.10	-0.23	0.83	2.59	7.65
Iraq	22.11	0.024	0.67	-0.0008	0.0006	-0.28	-0.44	0.73	0.29	0.86	2.74
Ireland	9.34	0.015	0.41	0.0001	0.0008	0.03	0.09	0.26	0.46	1.47	4.62
Israel	20.31	0.017	0.55	-0.0004	0.0007	-0.12	-0.24	-0.08	0.36	1.15	3.87
Italy	12.21	0.028	0.43	0.0000	0.0011	0.01	0.02	0.05	0.89	2.56	7.01
Jamaica	25.18	0.020	0.35	0.0000	0.0007	0.01	0.04	0.09	0.59	1.71	4.80
Japan	11.18	0.013	0.40	0.0006	0.0017	0.33	1.06	3.47	1.12	3.72	10.70
Jordan	18.56	0.015	0.62	0.0002	0.0015	0.08	0.22	0.70	0.72	2.61	8.69
Kazakhstan	6.00	0.024	0.80	0.0010	0.0023	0.46	1.48	5.02	1.35	4.65	14.33
Kenya	24.46	0.018	0.31	-0.0005	0.0004	-0.29	-0.48	0.50	0.29	0.82	2.39
Kuwait	25.61	0.025	0.54	-0.0008	0.0006	-0.35	-0.58	0.60	0.39	1.14	3.46
Kyrgyzstan	1.75	0.028	0.52	0.0003	0.0017	0.18	0.48	1.36	1.31	3.91	10.85
Laos	23.20	0.009	0.39	-0.0004	0.0005	-0.09	-0.07	0.78	0.19	0.65	2.34
Latvia	5.82	0.030	0.85	-0.0004	0.0007	-0.18	-0.40	-0.52	0.36	1.08	3.46
Lebanon	15.19	0.025	0.59	0.0009	0.0019	0.53	1.63	5.06	1.36	4.30	12.35
Lesotho	11.75	0.010	0.46	0.0008	0.0020	0.36	1.30	4.61	1.16	4.22	12.60
Liberia	25.66	0.009	0.22	0.0001	0.0009	0.03	0.09	0.26	0.66	2.07	5.76
Libya	22.34	0.033	0.36	-0.0012	0.0000	-0.91	-1.31	2.50	0.03	0.07	0.19
Lithuania	6.42	0.028	0.84	-0.0003	0.0008	-0.12	-0.27	-0.45	0.41	1.26	4.16
Luxembourg	9.07	0.028	0.65	-0.0006	0.0003	-0.29	-0.56	-0.12	0.19	0.54	1.60
Macedonia	10.31	0.013	0.54	0.0007	0.0019	0.28	0.96	3.46	1.08	3.92	12.04
Madagascar	22.87	0.021	0.28	-0.0003	0.0006	-0.20	-0.45	-0.75	0.55	1.54	4.14
Malawi	22.26	0.023	0.34	-0.0004	0.0007	-0.29	-0.62	-0.57	0.62	1.76	4.81
Malaysia	25.30	0.013	0.21	-0.0002	0.0006	-0.15	-0.31	-0.34	0.53	1.51	4.12
Mali	28.70	0.021	0.38	-0.0004	0.0009	-0.24	-0.50	-0.38	0.67	1.96	5.53
Mauritania	27.68	0.024	0.44	-0.0004	0.0008	-0.26	-0.54	-0.47	0.63	1.86	5.33
Mauritius	23.92	0.022	0.30	-0.0005	0.0002	-0.38	-0.70	0.15	0.13	0.34	0.92
Mexico	20.43	0.012	0.25	-0.0002	0.0009	-0.10	-0.21	-0.23	0.64	1.97	5.54
Moldova	9.37	0.020	0.78	0.0004	0.0016	0.17	0.50	1.68	0.81	2.85	9.51
Mongolia	0.15	0.028	0.66	-0.0003	0.0011	-0.16	-0.35	-0.57	0.68	2.11	6.52
Montenegro	8.54	0.020	0.48	0.0015	0.0026	1.05	3.33	9.64	2.09	6.42	17.50
Morocco	18.77	0.021	0.44	-0.0003	0.0009	-0.18	-0.38	-0.44	0.65	1.97	5.80
Mozambique	24.20	0.015	0.33	-0.0004	0.0007	-0.16	-0.31	-0.02	0.47	1.46	4.35
Myanmar	22.98	0.020	0.30	-0.0005	0.0004	-0.34	-0.61	0.25	0.29	0.80	2.24
Namibia	19.57	0.026	0.50	0.0004	0.0015	0.27	0.77	2.26	1.20	3.58	9.99
Nepal	15.13	0.018	0.38	0.0009	0.0020	0.59	1.82	5.34	1.61	4.86	13.15
Netherlands	9.71	0.024	0.65	-0.0006	0.0003	-0.24	-0.43	0.13	0.15	0.42	1.27
New Caledonia	21.43	0.012	0.36	0.0008	0.0015	0.44	1.45	4.62	1.02	3.39	9.73
New Zealand	10.16	0.002	0.39	0.0009	0.0017	0.23	1.17	4.78	0.70	3.18	10.35
Nicaragua	26.18	0.029	0.34	-0.0007	0.0001	-0.57	-1.05	0.32	0.08	0.22	0.58
Niger	27.60	0.008	0.57	-0.0007	0.0005	-0.05	0.13	1.74	0.14	0.51	2.12
Nigeria	26.87	0.016	0.30	-0.0004	0.0006	-0.23	-0.42	0.08	0.42	1.24	3.56
Norway	1.35	0.023	0.75	-0.0008	0.0004	-0.23	-0.36	0.62	0.19	0.56	1.80

Notes: We consider persistent increases in temperatures based on the RCP 2.6 and RCP 8.5 scenarios. The losses are based on $\Delta_{ih}(d_i)$, see equation (13), with $h = 16$, 36, and 86 (corresponding to the year 2030, 2050, and 2100, respectively) and $m = 30$.

Table A.7: Percent Loss in GDP per capita by 2030, 2050, and 2100 under the RCP 2.6 and RCP 8.5 Scenarios (continued)

	Key Variables in Equation (13)					Percent Loss in GDP per capita					
	$\bar{T}i$	$\widehat{b}^0_{Ti}$	$\widehat{\sigma}_{Ti}$	d_i		RCP 2.6 Scenario			RCP 8.5 Scenario		
				RCP 2.6	RCP 8.5	2030	2050	2100	2030	2050	2100
Oman	26.79	0.008	0.31	0.0002	0.0013	0.08	0.26	0.87	0.81	2.83	8.31
Pakistan	20.43	0.010	0.40	0.0002	0.0015	0.08	0.26	0.88	0.88	3.16	9.55
Panama	25.12	0.017	0.31	0.0000	0.0008	0.01	0.02	0.05	0.63	1.87	5.27
Papua New Guinea	23.80	0.007	0.19	0.0003	0.0011	0.15	0.45	1.44	0.82	2.55	6.99
Paraguay	23.72	0.005	0.50	0.0003	0.0014	0.06	0.23	1.02	0.49	2.21	8.01
Peru	19.96	0.007	0.32	0.0002	0.0012	0.05	0.16	0.55	0.66	2.46	7.61
Philippines	25.42	0.007	0.20	0.0005	0.0013	0.29	0.98	3.05	0.98	3.09	8.46
Poland	7.84	0.026	0.76	-0.0003	0.0008	-0.12	-0.27	-0.43	0.38	1.16	3.83
Portugal	15.20	0.010	0.42	0.0002	0.0013	0.07	0.22	0.72	0.68	2.46	7.75
Puerto Rico	23.53	0.006	0.30	0.0006	0.0013	0.24	0.89	3.16	0.71	2.62	7.92
Qatar	26.79	0.027	0.51	-0.0004	0.0008	-0.25	-0.54	-0.62	0.60	1.77	5.15
Romania	8.91	0.019	0.62	0.0002	0.0014	0.10	0.27	0.83	0.77	2.64	8.47
Russian Federation	-5.96	0.035	0.68	-0.0002	0.0014	-0.14	-0.34	-0.71	1.03	3.08	8.93
Rwanda	19.93	0.016	0.35	0.0001	0.0011	0.06	0.15	0.42	0.80	2.49	7.12
St. Vincent & Grenadines	26.69	0.012	0.29	-0.0005	0.0002	-0.19	-0.26	0.70	0.13	0.38	1.16
Samoa	26.24	-0.004	0.28	0.0008	0.0014	0.02	0.66	3.64	0.31	2.31	8.31
Sao Tome and Principe	25.69	0.024	0.29	-0.0001	0.0007	-0.04	-0.11	-0.27	0.69	1.88	4.97
Saudi Arabia	25.51	0.021	0.55	-0.0007	0.0006	-0.26	-0.38	0.78	0.34	1.05	3.35
Senegal	28.29	0.026	0.35	-0.0004	0.0006	-0.31	-0.67	-0.73	0.53	1.46	4.01
Serbia	9.96	0.016	0.54	0.0002	0.0014	0.09	0.25	0.78	0.79	2.74	8.66
Sierra Leone	26.20	0.016	0.24	-0.0004	0.0005	-0.25	-0.47	-0.03	0.41	1.16	3.22
Slovakia	7.64	0.020	0.61	0.0001	0.0013	0.06	0.17	0.50	0.71	2.36	7.54
Slovenia	7.80	0.030	0.59	0.0003	0.0015	0.22	0.61	1.76	1.10	3.33	9.50
Solomon Islands	26.85	0.010	0.18	0.0002	0.0009	0.12	0.35	1.04	0.77	2.23	5.98
Somalia	26.65	0.021	0.32	-0.0006	0.0003	-0.37	-0.65	0.41	0.22	0.59	1.66
South Africa	17.52	0.007	0.33	0.0001	0.0012	0.04	0.11	0.35	0.67	2.46	7.56
South Korea	11.07	0.008	0.49	0.0008	0.0019	0.30	1.15	4.34	0.96	3.73	11.68
South Sudan	27.35	0.031	0.43	-0.0008	0.0004	-0.52	-0.98	0.05	0.32	0.87	2.40
Spain	13.31	0.026	0.45	-0.0001	0.0010	-0.08	-0.19	-0.43	0.77	2.26	6.39
Sri Lanka	27.11	0.011	0.21	-0.0001	0.0006	-0.07	-0.17	-0.27	0.50	1.51	4.23
Sudan	27.34	0.029	0.38	-0.0009	0.0002	-0.63	-1.04	1.21	0.19	0.51	1.38
Suriname	26.21	0.004	0.34	0.0003	0.0012	0.07	0.26	1.06	0.54	2.26	7.42
Swaziland	20.33	0.017	0.43	-0.0008	0.0002	-0.29	-0.23	2.14	0.09	0.24	0.71
Sweden	2.27	0.021	0.89	-0.0005	0.0007	-0.14	-0.24	0.07	0.24	0.76	2.67
Switzerland	4.88	0.018	0.49	0.0008	0.0019	0.46	1.45	4.60	1.32	4.27	12.24
Syria	17.88	0.022	0.65	-0.0005	0.0007	-0.19	-0.37	-0.07	0.37	1.12	3.67
Tajikistan	3.08	0.000	0.57	0.0003	0.0017	0.01	0.06	0.38	0.43	2.38	9.35
Tanzania	22.65	0.010	0.31	-0.0003	0.0008	-0.09	-0.17	0.02	0.46	1.54	4.73
Thailand	26.22	0.005	0.31	-0.0002	0.0007	-0.03	-0.05	0.06	0.29	1.12	3.98
Togo	26.41	0.018	0.25	-0.0001	0.0008	-0.07	-0.18	-0.41	0.76	2.13	5.64
Trinidad and Tobago	25.62	0.024	0.30	-0.0005	0.0003	-0.36	-0.76	-0.56	0.24	0.64	1.74
Tunisia	20.08	0.037	0.43	-0.0011	0.0001	-0.82	-1.40	1.21	0.08	0.21	0.53
Turkey	11.24	0.014	0.70	0.0002	0.0014	0.07	0.20	0.64	0.60	2.26	7.98
Turkmenistan	15.67	0.025	0.67	0.0000	0.0012	0.00	-0.01	-0.01	0.72	2.30	7.19
Uganda	22.84	0.020	0.31	-0.0004	0.0005	-0.28	-0.56	-0.17	0.42	1.19	3.32
Ukraine	8.17	0.026	0.81	0.0002	0.0014	0.08	0.22	0.63	0.73	2.39	7.82
United Arab Emirates	27.22	0.016	0.48	0.0002	0.0015	0.08	0.22	0.65	0.92	3.10	9.31
United Kingdom	8.69	0.013	0.46	-0.0001	0.0007	-0.02	-0.05	-0.11	0.34	1.16	3.97
United States	6.94	0.015	0.36	0.0004	0.0016	0.20	0.60	1.88	1.20	3.77	10.52
Uruguay	17.49	0.015	0.35	0.0002	0.0009	0.09	0.24	0.70	0.65	2.05	6.00
US Virgin Islands	26.79	0.023	0.45	-0.0009	-0.0002	-0.41	-0.50	1.89	-0.13	-0.30	-0.54
Uzbekistan	12.84	0.021	0.69	0.0007	0.0019	0.30	0.93	3.11	1.11	3.79	11.72
Vanuatu	24.75	0.028	0.33	-0.0005	0.0002	-0.38	-0.83	-0.87	0.21	0.55	1.48
Venezuela	25.00	0.016	0.30	0.0000	0.0010	0.00	0.00	-0.01	0.82	2.45	6.74
Vietnam	23.20	0.005	0.32	0.0000	0.0009	0.00	0.01	0.02	0.38	1.51	5.15
Yemen	24.56	0.035	0.60	-0.0007	0.0004	-0.40	-0.82	-0.61	0.27	0.74	2.12
Zambia	21.17	0.019	0.47	0.0003	0.0015	0.18	0.51	1.56	1.06	3.40	9.82
Zimbabwe	21.24	0.014	0.47	0.0001	0.0013	0.04	0.12	0.35	0.76	2.62	8.15

Notes: We consider persistent increases in temperatures based on the RCP 2.6 and RCP 8.5 scenarios. The losses are based on $\Delta_{ih}(d_i)$, see equation (13), with $h = 16$, 36, and 86 (corresponding to the year 2030, 2050, and 2100, respectively) and $m = 30$.