Growth at Risk From Climate Change

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Abstract

How will climate change affect risks to economic activity? Research on climate impacts has tended to focus on effects on the average level of economic growth. I examine whether climate change may make severe contractions in economic activity more likely using quantile regressions linking growth to temperature. The effects of temperature on downside risks to economic growth are large and robust across specifications. These results suggest the growth at risk from climate change is large—climate change may make economic contractions more likely and severe and thereby significantly impact economic and financial stability and welfare.

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1. Introduction

Climate change is perhaps the central economic and social challenge of the 21st century. Changes in the climate may impact the health, economic productivity, and community fabric of everyone on the planet. A central question is how climate change will affect risks to economic activity. For example, Weitzman (2014) and Barro (2015) highlight how welfare implications of climate change hinge importantly on the degree to which climate change makes large contractions in economic activity more likely. But empirical macroeconomic analysis has often focused on the impact of climate change on the average growth rate of economic activity, not the distribution of risks (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Kalkuhl and Wenz, 2020; Newell, Prest, and Sexton, 2021).

Climate change may lead to greater downside risk to economic activity—that is, shifts in the severity of economic downturns (or growth shortfalls) associated with a warmer planet or other dimensions of climate change. For example, a hotter average temperature could raise the risk of factors that lead to an economic contraction—poor productivity across sectors, disturbances to trade or production networks, or other factors. Previous research has not quantitatively examined these possibilities in detail, although work—especially work around climate-related financial risks—has suggested the possibility that risks associated with fluctuations, rather than the central tendency, may be associated with climate change (e.g., Litterman, 2020; Financial Stability Board, 2020). Scenario analysis of the risks associated with climate change have incorporated effects on the average pace of economic growth (e.g., Network for the Greening of the Financial System (NGFS) as described in Bertram et al, 2021). Consideration of tail risks from climate change is more closely related to scenario analysis than consideration of links between climate change and average growth, as typical scenario analysis considers adverse tail outcomes, suggesting a focus on tail effects may be valuable.[1]

This analysis herein explores the link between climate change and risks to economic activity using quantile regressions, as in the literature on Growth at Risk (e.g., Adrian, Boyarchenko, and Giannone, 2019; Kiley, 2022). The Growth-at-Risk approach is a relatively new one, with substantial recent research contributions (e.g., Plagborg-Møller, 2020; Brownlees and Souza, 2021; and Adrian et al, 2022) and policy applications (e.g., IMF, 2017). The value of the approach is its focus on adverse tail events to

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[1] NGFS (in Bertram et al, 2021) uses the effects from Kalkuhl and Wenz (2020) to include an effect on GDP from physical risks in its scenarios. Kalkuhl and Wenz (2020) use least squares to estimate effects, and hence focus on the impact on the central tendency. The focus on the tails herein more directly focuses on risk, as in the Growth at Risk approach promoted by the IMF (2017).

economic activity. As climate change may affect downside risks to economic activity, for example associated with natural disasters (e.g., the effect of a prolonged drought on agriculture), the Growth-at-Risk approach offers new insights relative to previous work.

The effect of climate on the distribution of economic growth is considered using fluctuations in temperature—i.e., using weather rather than climate. The results show a very strong impact of temperature on Growth at Risk: downside risk to GDP growth, as measured by the lower quantiles of the growth distribution, are magnified with an increase in temperature to a much more sizable degree than the central tendency of the distribution of growth is affected. The impact of temperature on the lower decile of the growth distribution is 50 percent (or more) larger (in absolute value) than the effect on the central tendency of the distribution. Effects of this magnitude are sufficient to imply very large shifts in the distribution of economic growth, as discussed below for a small selection of countries and as illustrated in some detail for India.

Previous literature: Weitzman (2014) and Barro (2015) emphasize how tail outcomes associated with climate change may dominate the way in which climate change affects economic welfare. Lemoine (2021a) considers similar issues. Nordhaus (2011) highlights the importance of correlations between adverse climate and macroeconomic outcomes in assessing welfare impacts of climate change in an integrated assessment model. van den Bremer and van der Ploeg (2021) examine how uncertainty about risks associated with climate change may affect estimates of the social cost of carbon, but their analysis focuses on uncertainty regarding climate outcomes and the consequent uncertainty in average growth. They do not consider how an increase in risks associated with fluctuations in growth around its average—and especially an increase in the risk of severe economic contractions stemming from climate change—may impact welfare and risk. The analysis herein may be able to inform such assessments in the future. Empirical work on how climate change may affect the risk of large adverse events—growth disasters—is essentially non-existent, and the analysis herein begins to fill that void.[2]

One reason that empirical work on growth disasters associated with climate change is limited is that a focus on tail outcomes is not typical in macroeconomics. The analysis herein builds on research using quantile regressions to consider tail risks following IMF (2017), Adrian, Boyarchenko, and Giannone

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[2] Researchers have explored other risks to economic activity associated with climate change. For example, Lemoine and Kapnick (2016) and Kahn et al (2019) consider the effect of alternative climate pathways (that is, the risks associated with uncertainty about climate change) for economic activity in different regions over the 21st century using estimated links between climate pathways and the expected growth rate or level of economic activity.

(2019), and Kiley (2022). The type of equations used herein—equations linking growth and temperature has been used elsewhere to assess the possible effects associated with climate change on average economic growth (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Kalkuhl and Wenz, 2020; and Newell, Prest, and Sexton, 2021). The advantages and disadvantages of this approach have been explored (Dell, Jones, and Olken, 2014; Hsiang, 2016; Lemoine, 2021b) and are briefly discussed below.

The previous empirical literature linking climate change and the central tendency of economic growth has played an important role in policy discussions. Carleton and Greenstone (2021) and Rennert et al (2021) note how the "damage functions" associated with this empirical approach have been discussed in the context of estimating the social cost of carbon, while emphasizing that the reduced-form nature of the empirical approach makes such a use challenging. The work herein, while similarly reduced form in nature, expands the evidence on climate change impacts and potential social costs by examining how climate change may affect the likelihood of economic growth disasters.

The previous work highlighted is mainly macroeconomic in nature: however, microeconomic studies have also shown adverse effects of temperature/climate change on economic activity, such as adverse effects on labor productivity such as in Somanathan et al. (2021) and adverse effects on agricultural yields in Schlenker and Roberts (2009); these microeconomic studies both confirm the adverse effects highlighted in macroeconomic analyses and provide suggestions for the channels that lead to estimated empirical impacts (e.g., productivity and agricultural channels).

Importantly, the analysis herein is solely empirical and does not highlight mechanisms that main explain the empirical results—although the findings on agricultural, which shows an especially pronounced increase in downside risk associated with higher temperatures, is suggestive of mechanisms. The evidence for effects on economic risk—that is, for changes in the distribution of likely economic outcomes around central tendencies in addition to the effects on central tendencies documented in previous work—appears strong, which suggests that additional analyses that link empirical findings to plausible mechanisms is important.

Structure of the remaining sections: Section 2 discusses the framework for assessing growth at risk from climate change, including the use of weather to gauge climate impacts, key aspects of the quantile regression approach, and the data used in this study. Section 3 presents results and robustness exercises. Section 4 illustrates growth at risk from climate change, and section 5 concludes.

2. Data and approach

2.1 Data

The approach extends the analysis of Dell, Jones, and Olken (2012a), Burke, Hsiang, and Miguel (2015), Burke, Davis, and Diffenbaugh (2018), Kalkuhl and Wenz (2020), and Newell, Prest, and Sexton (2021) to consideration of links between temperature and the entire distribution of yearly economic growth. The analysis draws data from the replication codes of Burke, Davis, and Diffenbaugh (2018). Economic data is drawn from the World Bank's *World Development Indicators*. The focus herein is on the percent change in real GDP per capita (on an annual basis).

The data on weather focuses exclusively on temperature and does not consider the effects of precipitation. (As in Dell, Jones, and Olken, the effects of precipitation were not important for the effects analyzed herein—and hence are omitted.) The temperature data is from the *Terrestrial Air Temperature and Precipitation: 1900–2006 Gridded Monthly Time Series, Version 1.01* (Matsuura and Willmott 2012) and is aggregated to the country level using population weights for areas within a country.

Overall, the data include 124 countries, with the sample confined to countries with at least 30 years of data on the percent change in real GDP per capita and weather. Regressions focus on the period from 1961-2010, reflecting data availability.

Two aspects of the data merit mention (and are discussed more fully elsewhere, e.g., Dell, Jones, and Olken, 2012a). First, the world became warmer over the 50 years covered in the data, with the average temperature increasing about 1°C from the 1950s to the turn of the century. Second, there is a negative cross-sectional correlation between real GDP per capita and temperature—hotter countries tend to be poorer. The negative correlation between income and temperature has been observed for a long time (Montesquieu, 1750). This correlation has spurred debate on how to identify a causal link between temperature and income (e.g., Sachs and Warner, 1997; Gallup, Sachs, and Mellinger, 1999; Acemoglu, Johnson, and Robinson, 2002; and Sachs, 2003).

The tendency for rich countries to be cooler than poor countries can be seen in table 1, where the average temperature difference between Western Europe and its offshoots and other regions of the world is clear. Table 1 presents summary statistics for the percent change in real GDP per capita and temperature by regions of the world. There is substantial within country variation in the year-to-year percent change in real GDP (that is, the within country variation is comparable to the overall variability in the sample across all observations). This is consistent with business cycle fluctuations being a first-order concern and hence with the focus of the analysis herein in risks to real GDP growth. Second, most of the variation in temperature in the sample is across countries—that is, the within-country standard deviations of temperature are relatively small compared to between-country differences. For example, the average temperature over the sample in the United States is 13.7°C while the average temperature in Nigeria over the sample is 26.8°C. In contrast, the standard deviations of annual temperature across years in the United States and Nigeria both equal 0.4°C. The difference between average temperature in the United States and Nigeria is much larger than the variation within each country. Nonetheless, the standard deviation of temperature within country from year-to-year is sufficient to be economically important. Generally, these standard deviations are on the order of 0.5°C -0.7°C. This magnitude of variation, with a two standard deviation move of 1°C to 1-1/2°C, is similar in magnitude to the anticipated increase in temperature associated with climate change in coming decades.

A final data issue is the heterogeneity in the experience across countries in the percent change in real GDP per capita, with some countries experiencing significant outliers. To see this, a scatterplot of the data of interest—the percent change in real GDP per capita against temperature in the year—is useful. Figure 1 presents this scatterplot, with different colors/markers highlighting regions of the world. The scatterplot highlights how most of the variation in economic growth is independent of temperature. It also shows that regions of the world are quite different, with “Western Europe and Offshoots” spanning from very low temperatures (e.g., Greenland and Iceland, for example) to relatively high temperatures (e.g., Israel and Puerto Rico) while “Sub Saharan Africa” is primarily relatively hot. More significantly, there are some large growth outliers – economic catastrophes (GDP falling more than 20 percent in a year) or economic miracles (GDP rising more than 20 percent in a year). These patterns suggest the results may be sensitive to outliers. Importantly, many of the outliers occur around civil wars or extreme political changes (e.g., Algeria in the 1960s, Liberia and Rwanda in the 1990s, Georgia in the 1990s) or around discovery of oil in small countries (e.g., Equatorial Guinea in the 1990s and others). Table 2 reports the countries in the analysis and highlights those that experience growth outliers, defined as a year in which growth was more than three standard deviations from the global mean. The empirical analysis will examine the sensitivity of results to these outliers.

2.2 Empirical Approach

Our empirical approach focuses on the distribution of the percent change in real GDP per capita within a country. Denoting the cumulative distribution function of the percent change in real GDP per capita in country j in period t conditional on time t information I(t) as $G_j(\Delta y(t)|I(t))$, the Z$^{\text{th}}$ conditional percentile is

(1) $$Q_j^{0.Z}(t) = G_j^{-1}\left(0.Z\middle|I(t)\right) = \inf\{\Delta y(t): G(\Delta y(t)|I(t)) \geq 0.Z\}.$$

For example, the 10th conditional percentile of the percent change in real GDP per capita, a gauge of the position of the lower (or adverse) tail of outcomes, is the smallest value of the change in real GDP per capita in period t such that there is a 10 percent (or greater) probability that the change in real GDP per capita will be less than the value.

To examine the link between temperature and the distribution of the percent change in real GDP per capita, the following equation, linking temperature to the percent change in real GDP per capita, is estimated using quantile regression:

(2) $$\Delta y(t,j) = a_j + YEAR(t) + G(TIME(t,j)) + F\big(T(t,j)\big).$$

In equation (2), $\Delta y(t,j)$ is the percent change in real GDP per capita in period t in country j and $T(t,j)$ is average temperature in period t in country j. The quantile regression includes country fixed effects (a_j) and a vector of quadratic country-specific time trends ($G(TIME(t,j))$) and year dummy variables, ($YEAR(t)$). This general approach has been used previously in least-squares regressions (e.g., Burke, Hsiang, and Miguel, 2015).

The analysis considers several choices for $F\big(T(t,j)\big)$ to ensure the robustness of the results.

- **Quadratic in temperature:**

  (3) $$\boldsymbol{F\big(T(t,j)\big) = a_{1,0}T(t,j) + a_{1,1}T(t,j)^2.}$$

  This specification allows the data to flexibly fit a relationship between growth and average temperature. For example, under this specification, growth could be increasing in temperature for countries with a “cool” starting temperature and decreasing in temperature for countries with an initially “hot” temperature. This is the preferred specification in Burke, Hsiang, and Miguel (2015) and will be the main specification used herein.
- **Quadratic in temperature with temperature change interactions:**

(4) $$\boldsymbol{F\big(T(t,j)\big) = a_{1,0}T(t,j) + a_{1,1}T(t,j)^2 + a_{2,0}\Delta T(t,j) + a_{2,1}T(t,j)\Delta T(t,j).}$$

This specification adds the change in temperature from the previous year and the interaction of the level of temperature and its change from the previous year to the quadratic specification. Such an approach may eliminate effects from short-run increases in temperature that would be unlikely to be carry over to temperature increases associated with climate change; that is, this specification allows for an impact on economic growth of a change in temperature, rather than a deviation of a year's temperature from a country's average yearly temperature (which, owing to country-fixed effects, is the relationship analyzed with the levels specification). This approach is adopted in Kalkuhl and Wenz (2020) and is considered for robustness.

- **Linear & low-income effect of temperature:**

(5) $$\boldsymbol{F\big(T(t,j)\big) = a_{1,0}T(t,j) + a_{1,1}T(t,j)I_{low\ income}}$$

This linear specification does not differentiate impact based on the level of temperature. However, it differentiates effects across low-income and high-income countries. $I_{low\ income}$ is an indicator function equaling 1 if a country is below the median across countries in 1960, which allows the effect of temperature to differ across "poor" and "rich" countries. This specification is adopted in Dell, Jones, and Olken (2012) and is considered for robustness.

Several aspects of these specifications are noteworthy. First, the investigation considers the link between the distribution of the percent change in real GDP per capita and weather variables controlling for country fixed effects and time/region fixed effects. This specification eliminates the "permanent" component of weather via fixed effects, and hence may control for concerns regarding the link between the average temperature and the level of income across countries. As a result, researchers have argued that this approach may be suggestive of a causal link between weather and economic activity (e.g., Dell, Jones, and Olken, 2012a; Dell, Jones, and Olken, 2014; Burke, Hsiang, and Miguel, 2015; Hsiang, 2016), while acknowledging substantial conceptual and econometric challenges extrapolating empirical links associated with weather to those that may accompany climate change (Lemoine, 2021b).

Newell, Prest, and Sexton (2021) highlight how regressions involving the link between growth rates and temperature can imply very large effects on the level of GDP over long time periods from an increase in temperature associated with climate change. They further consider regressions like the quadratic specification and the linear/low-income specification as well as many other specifications that link changes in temperature and economic growth. They find that the data do not speak clearly on whether a specification involving the level of temperature or the change in temperature fits better—and these differences are very important for estimating long-run effects on the level of GDP (as climate change may involve a one-time upward shift in temperature, implying that a specification linking economic growth and the change in temperature implies much smaller long-run effects on the level of GDP than a specification involving the level). Finally, Newell, Prest, and Sexton (2021) emphasize specification uncertainty and discuss the need to place empirical results in context with related, but different, modeling approaches such as integrated assessment models. The subsection on robustness considers some of the issues raised by Newell, Prest, and Sexton (2021) in more detail.

The empirical research of the previous paragraph focuses on least-squares regressions and thereby estimates an average (mean) relationship, rather than describing effects on the distribution (which may differ from a simple shift in the central tendency). The interest herein is on the degree to which weather (climate) may alter the distribution of outcomes. As a result, the analysis turns to quantile regressions. However, quantile regressions in a panel setting have been a challenge to implement (Canay, 2011; Kato, Galvao, and Montes-Rojas, 2012; and Machado and Santos Silva, 2019) and hence have not been widely employed. The approach herein follows the quantiles-via-moments method of Machado and Santos Silva (2019), using their xtqreg command in Stata.

Before turning to results, a bit more review of quantile regressions may help some readers. While quantile regressions are less widely used in macroeconomics than least squares, the GDP at Risk literature has used the approach extensively (e.g., Cecchetti and Li, 2008; Adrian, Boyarchenko, and Giannone, 2019; IMF, 2017; and Kiley, 2022). Moreover, the intuition is straightforward. Focusing on the standard case (and referring the reader interested in the complications associated with a panel setting to Machado and Santos-Silva, 2019), quantile regression weights errors in the projections more heavily for errors near the quantile of interest—by placing larger weights on negative errors for quantiles in the lower tail of the distribution and larger weights on positive errors for quantiles in the upper tails of the distribution. To see this more formally, define the error terms consistent with equation (2) as $e(t)$ and note that typical approach to quantile regression for a given quantile q minimizes the loss function

$$L = \sum_{t=1}^{T} q\langle e(t)I(e(t) > 0)\rangle + (q-1)\langle e(t)I(e(t) < 0)\rangle$$

where $I(.)$ is the indicator function (i.e., $I(e(t) < 0)$ equals 1 when $e(t) < 0$). For low quantiles (q below 0.5), negative errors receive larger weight than positive errors. Alternatively, the 50th percentile quantile regression – the median regression – finds the coefficients that minimize the least absolute deviation of the errors from the projection (rather than least squared deviation in ordinary-least squares regression). This approach places relatively more weight on deviations close to the center of the error distribution (e.g., close to the estimated median) than least squares, as absolute deviations are relatively smaller for larger errors than are squared errors. (For a formal discussion of quantile regression, see Koenker and Hallock, 2001). This intuition highlights why uncertainty regarding tail relationships (q far from 0.5) is challenging: such relationships are uncovered by placing greater weight on a subset of observations in the neighborhood of the quantile of interest, which is akin to a reduction in sample size.

3. Temperature and Growth at Risk

3.1 Least squares and median (least absolute deviation) regression results

To draw comparison with the earlier literature and set a baseline with which to compare the full set of quantile regressions, the link between temperature and the central tendency of growth is examined by least squares and median regression. The first column of table 3 reports results for equation 2 using least squares. The sixth column—labeled (5) for the 5th decile, Z equal to the 50th percentile—reports results for median (least absolute deviations) regression for the three specifications of $F\big(T(t,j)\big)$. Standard errors are obtained via the bootstrap, clustering at the country level. The results echo those from earlier work and demonstrate that, in this case, least squares and median regression yield very similar effects of temperature on economic growth. In particular, the adverse impact on economic growth is confined to hot countries (upper panel and middle panel) or poor countries (lower panel)—with the central tendency of growth falling somewhat more than 1 percentage point for a 1°C increase in average temperature in a year (for both the mean (least squares) and median). Note that the effects of temperature on growth are remarkably similar across the specifications, subject to consideration of a hot country (e.g., mean temperature of 25.64°C) and a poor country. This is reassuring, and perhaps not surprising. A mean temperature of 25.64°C corresponds to the 75th percentile of mean temperature between the years 1986-2005 across countries, implying that 25 percent of countries have an average annual temperature at or above this value. As noted in table 1, poorer regions of the world tend to be hotter, so in general the set of countries with these characteristics will be similar to the set of poor countries. Putting these facts together, an empirical specification focused on poor countries will also focus on hot countries.

3.2 Quantile regressions results

The analysis now turns to the link between temperature and the distribution of economic growth. Table 3 reports quantile regressions for each decile from the 10th to the 90th, with the 10th decile in column 2 (labeled (1) for the first decile) and the 90th in column 10 (labeled (9) for the ninth decile). The upper rows report results using the baseline quadratic specification.

The results are stark: Downside risks to growth (the 10th percentile) are more strongly linked to temperature than the central tendency or upside risks (which are unrelated to temperature.) The differences are sizable. The lower tail of the distribution of economic growth (10th percentile) has an estimated relationship with temperature in poor countries that is 50 percent larger than the relationship for the central tendency (e.g., a marginal effect associated with a 1°C increase in temperature of -1.9 percentage point on the 10th percentile and -1.3 percentage point on the median); the impact on the 10th percentile is double that on the 90th percentile, highlighting a sharp increase in downside risk associated with the overall downward shift in the growth distribution associated with hotter temperatures.

The middle and bottom panels of table 3 report the results for the two alternatives to the quadratic specification. The qualitative and quantitative results are broadly similar—downside risks to economic growth are much more strongly linked to temperature than upside risks.

Specifically, allowing for effects of the short-run change in temperature weakens the link between temperature and growth (middle panel)—but this weakening is much more notable for the effect in the median regression or upper quantiles. In contrast, the effect in the 10th and 20th percentile regressions is very similar in the middle rows as in the upper rows. In addition to a modest weakening in the coefficients, the statistical significance of the results falls somewhat, with the most notable declines in the tails (as is expected given the challenges associated with estimating tail relationships).

Adopting a linear-in-temperature specification that differentiates between low- and high-income countries also does not alter the main results—the estimated link between the 10th percentile and temperature is about 50 percent larger than the effect on the central tendency in the bottom rows on table 3 and very similar to the effects in the quadratic specification. The impact effect on the 10th percentile is triple that on the 90th percentile, illustrating again the sharp increase in downside risk to growth associated with warmer temperature. The statistical significance of the results remains at conventional levels.

3.3 Robustness checks

The results above demonstrate the robustness of the results to the alternative specifications considered in Dell, Jones, and Olken (2012), Burke, Hsiang, and Solomon (2015), and Kalkuhl and Wenz (2020). Three additional issues, raised in earlier work and most clearly discussed in Newell, Prest, and Sexton (2021), are important: the magnitude of impacts and implications for long-run projections, the sensitivity of results to treatment of low-frequency shifts in growth rates across countries, and the effects on agricultural vs. nonagricultural GDP.

The estimated magnitude of the link between temperature and economic growth across the estimated quantiles are large: for example, a decline in the growth rate of real GDP per capita greater than 1 percentage point for the median regression, extrapolated for a permanent 1-degree Celsius increase in temperature, implies that the level of real GDP per capita would be more than 50 percent lower than without the temperature change after 50 years. Newell, Prest, and Sexton (2021) note this effect is large relative to estimates from integrated assessment models. More simply, the regressions specify the dependent variable as the one-year growth rate and hence emphasize high-frequency (business-cycle) information, and it may be inappropriate to forecast such effects over decades. This observation suggests a robustness check focused on the change in detrended real GDP as in equation (3)

$$\textbf{(3)} \qquad \Delta y^{detrended}(t,j) = a_j + A_D D + b y^{detrended}(t-1,j) + F\big(T(t,j)\big).$$

In equation (3), the long-run effect of temperature on the level of real GDP, assuming b<0, is $\frac{F(T(t,j))}{1+b}$, a value that does not grow with the time horizon. (This assumes that the trend in real GDP is otherwise unaffected by temperature/climate.) The alternative specification, by focusing on detrended GDP for the quantile regressions, also emphasizes that the interest is primarily in one-year growth effects (including growth disasters in the adverse tail)—not cumulative level effects. Admittedly, this approach may only partially address concerns associated with long-run effects and introduces other concerns, such as the robustness to alternative means of detrending real GDP and issues associated with dynamic panel regressions. These concerns, while valid, are not explored as this exercise is merely one robustness check. The upper panel of table 4 reports results for this specification (where log real GDP per capita is detrended for each country with a quadratic trend) when $F\big(T(t,j)\big)$ Is the quadratic specification. The short-run effects on growth are very similar to table 3 (and b (not reported) equals about -0.125 for all quantiles, implying a long-run level effect about 8 times the reported impact effects).

A second issue is the sensitivity of results to treatment of low-frequency elements of real GDP growth. Newell, Prest, and Sexton (2021) highlight how coefficient estimates are generally much smaller and/or imprecisely estimated if the quadratic time trends included in table 3 are not included in least squares regressions. The next three panels of table 4 explore this issue for the quantile regressions, as outlined in the following bullets.

- **Specification without country-specific quadratic time trends**: As in Newell, Prest, and Sexton (2021), dropping the quadratic time trends substantially alters results—the temperature impacts are small and imprecisely estimated for least squares and all quantile regressions. Note that these specifications involve a great deal of noise—for least squares, the within R^2 is 0.00.
- **Specification without country-specific quadratic time trends and with post-1990 country specific dummy**: Macroeconomists are familiar with significant low-frequency variation in the growth of real GDP per capita—for example, growth in the United States was much higher pre-1970s, and many countries have experienced demographic transitions, shifts in policy regime, or changes in productivity trends that may affect economic growth at a low frequency. To account for these low frequency shifts while deleting country-specific time trends as suggested by Newell, Prest, and Sexton (2021), an alternative with a country specific post-1990 dummy was included. These results are essentially identical to the baseline results above—demonstrating the potential importance of considering country-specific low-frequency movements in economic growth.
- **Specification without country-specific quadratic time trends and using only 1990 data**: An alternative to a country specific post-1990 dummy is to use only post-1990 data, as in the next panel. These estimated impacts of temperature across quantiles are very similar to the baseline results, but the standard errors are larger when the sample size is reduced in this manner.

All told, these robustness checks demonstrate the sensitivity of results to accounting for low frequency trends in economic growth. On balance, a reasonable interpretation is that the results are robust to alternative methods of accounting for this low-frequency component of growth—as in the baseline specifications or the two robustness cases involving a post-1990 dummy or post-1990 data—although researchers may disagree on this conclusion.

A third issue is the degree to which the results reflect impacts on growth in agricultural vs. nonagricultural real GDP per capita, the subject of the final two panels of table 4. The results on agricultural GDP show large and very statistically significant effects. Moreover, the differential effects across quantiles are in line with the growth at risk narrative: Downside risks to growth in agricultural GDP linked to temperature are very large relative to the effect on the median, highlighting how higher temperatures may raise the risk of growth disasters. In contrast, growth in nonagricultural GDP does not show a statistically significant link. Some researchers may find this finding reassuring, as it is plausible that agricultural output and risks are linked to temperature and hence points to plausible mechanisms behind the empirical results. That said, the literature (Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Newell, Prest, and Sexton, 2021) has debated the effects on nonagricultural GDP. The findings herein on the importance of agricultural GDP echoes the results of Newell, Prest, and Sexton (2021) most closely, as they find that the effects of temperature on agricultural GDP are more robust than other results in the literature.

3.4 Outliers and Heterogeneity in GDP Growth Experiences Across Countries

Another important robustness check is the sensitivity of results to outliers and the significant heterogeneity in growth experiences across countries. As highlighted in figure 1, there are some large growth outliers, often related to political changes or natural resource discoveries in small economies. The treatment of outliers is not obvious—for example, outliers may provide a lot of information in a regression. However, the role of events that seem (at least somewhat) independent of temperature suggest that approaches that examine the sensitivity to outliers are useful.[3]

Table 5 explores the sensitivity of the results to outliers in two ways, for both real GDP and agricultural GDP (considering the strong results for agricultural GDP in the previous section). The middle panel explores the sensitivity to outliers by deleting from the analysis all countries with an outlier. The specification of the equation is the same as in the baseline quadratic specification (with the same fixed effects and trends) in the upper panel of table 3. The results are reported in the same manner as in tables 3 and 4—effects on growth in a hot country from least squares and quantile regressions. The bottom panel keeps the full sample of countries but standardizes real GDP growth within a country before the regression; in this case, all countries real GDP growth data have a mean of zero and a standard deviation of one, which should diminish the effect of outliers. Finally, the upper panel repeats the baseline results from tables 3 and 4 for real GDP and agricultural GDP, to facilitate the comparisons.

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[3] While political turmoil may be independent of temperature, research has documented a link between sharp declines in economic output and violent conflict (Collier and Hoeffler, 2004; Collier, Hoeffler, and Rohner, 2009; Kim and Conceição, 2010)—with uncertainty about the direction of causality—and it is plausible that temperature, drought, agricultural shortfalls, and famine are part of the relationship, implying that such outliers should not necessarily be excluded. These complexities are topics for other research.

The results are clear. As shown in the middle panel, deletion of countries with outliers has essentially no effect on the results for least squares or quantile regressions. This is especially the case for overall real GDP, where the estimated effects of temperature are extremely close to the results from table 3. It is also the case for agricultural GDP: the pattern of estimates is very similar, although the point estimates differ somewhat.

The story is similar when the dependent variables (growth in real GDP or agricultural GDP per capita) are standardized (the lower panel). In this case, the estimated effects need to be multiplied by the standard deviations of the dependent variable to be expressed in units comparable to the units in the other tables—which is how table 5 presents the results. Again, the patterns and magnitudes of coefficients are very similar, suggesting that the outliers are not unduly influencing the results in this analysis.

3.5 Takeaways and Caveats

These results point to several takeaways. First, the results in the literature on average relationships may understate the degree to which an increase in temperature associated with climate change may lead to adverse effects on economic activity. Specifically, the quantile regressions highlight how climate change may increase the risk of very poor growth outcomes.[4] Second, an increase in average temperature associated with climate change may increase the volatility of economic growth and lead to additional downside skew in year-to-year fluctuations in economic growth, as the empirical relationship between temperature and downside risks to growth is strong, without a compensating apparent relationship to upside risks to growth.

At the same time, it is important to be cautious in such interpretations, as the short-run effects identified in these regressions may not extrapolate to changes in temperature associated with climate change. The empirical relationships herein are based on year-to-year fluctuations of temperature in a country—not long-run changes that may be experienced in the future. In addition, countries may be able to take mitigating steps—adapting to climate change and lessening adverse impacts. This caveat is well known (Dell, Jones, and Olken, 2014; Hsiang, 2016) and calls for more research. Finally, the strongest results are for agricultural output and the importance of agricultural output has generally been declining, which may limit the degree to which extrapolation of regression results to the future is

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[4] Growth disasters may lead to a variety of adverse impacts. For example, research has documented a link between sharp declines in economic output and violent conflict (Collier and Hoeffler, 2004; Collier, Hoeffler, and Rohner, 2009; Kim and Conceição, 2010).

appropriate. All these considerations point to a role for structural modeling to examine the growth-at-risk-from-climate-change issues identified herein.

4. Illustrating Growth at Risk from Climate Change

The impact of the regression results on the distribution of economic growth is illustrated for representative countries in Western Europe and its offshoots (the United States), Latin America (Brazil), Sub-Saharan Africa (Nigeria), and Southeast Asia (India). These countries are chosen because they are large and illustrate key aspects of the results.

In each case, the impact on the distribution of economic growth under temperature projections consistent with a high emission scenario (Representative Concentration Pathway (RCP) 8.5) is considered. This high emission scenario may be an upper bound should countries' policy commitments come to fruition. An alternative RCP projection that represents a plausible lower bound (RCP 2.6) is considered below.

Table 6 presents results. The United States is a relatively temperate country. As a result, the impact on the 10th percentile, median, and 90th percentile of the percent change in real GDP per capita is relatively modest in both the quadratic and linear specification. Moreover, the United States is a high-income country, and the estimated coefficient for high-income countries in the linear/low-income specification is positive, implying that a higher temperature shifts upward the distribution of economic growth. Note that this positive effect is not statistically significant, as in Dell, Jones, and Olken (2012).

Brazil is a relatively warm and high-income country. As a result, the results for the quadratic and linear/low-income specifications are quite different. These differences illustrate the importance of understanding the appropriate empirical specification: For example, the linear/low-income specification may accurately reflect an ability of high-income countries to adapt to the economic impact of climate change with modest effects on real GDP growth; alternatively, the small effect on high-income countries in this specification may capture the fact that high-income countries have smaller agricultural sectors (relative to the size of their economies) and temperature effects on agricultural risks are larger. Conversely, the quadratic specification may better capture the differences associated with a cool country warming versus a hot country warming. These issues, while critical, are beyond the focus herein.[5] More generally, the finding in the subsection on robustness showing that agricultural output may be the primary channel of transmission suggests differential impacts across countries based on the size of the agricultural sector—an issue that may require structural modeling.

The results for India and Nigeria—two large, hot, and low-income countries—illustrate the core results of the quantile regression approach to growth at risk from climate change. In both cases, an increase in temperature is expected to dramatically increase the downside risk to economic growth—lowering the 10th percentile of real GDP growth per capita by 3½ percentage points. The effects on the median and 90th percentile of growth are also sizable. Overall, the distribution of economic growth shifts down and downside risk increases sizably.

The effect on the distribution can be illustrated by presenting probability density functions implied by the quantile regression results. Figure 2 summarizes the impact of higher temperatures on Growth at Risk visually through a presentation of the distribution of the percent change in real GDP per capita in India for three cases under the quadratic specification for the quantile regressions. The three cases are the following.

- The distribution implied by the historical data from 1986 to 2005, as indicated by the estimated quantile regressions and average temperature over this period (i.e., as implied by fitting a distribution to the quantiles implied by equation 2 using the estimated coefficients in table 3).
- The distribution implied for 2040-59 under a low emission scenario (Representative Concentration Pathway 2.6), where an ensemble of models implies a 1.1°C temperature increase.
- The distribution implied for 2040-59 under a high emission scenario (Representative Concentration Pathway 8.5), where an ensemble of models implies a 1.9°C temperature increase.

A noted above, the two RCP pathways may represent lower and upper bounds (given current knowledge and projections). The results for India are representative of those for low-income countries: for example, its projected rise in temperature by 2040-59 is within the range expected for many countries.[6]

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[5] These issues are complex and require study. Note that Clark (2021) highlights the impact on work of the high temperatures experienced in the upper northwest of the United States and in the British Columbia region of Canada in June 2021.

[6] Data on temperature projections for RCP pathways associated with an ensemble of models are taken from the World Bank, https://climateknowledgeportal.worldbank.org/ .

In particular, the shifts shown for India would be similar for many countries in the sample that are hot and low income.

The distributions are estimated by fitting a kernel density to 19 quantiles implied by the estimated quantile regression, with the quantiles spanning from 0.05 to 0.95 in 0.05 increments. (Note this set of quantiles is larger than those reported in table 3). Specifically, the 1986-2005 density reflects the average fitted values for India implied by equation 2 given temperature over the period and the country fixed effects and the country/time trend interactions. The shifted distributions reflect the higher temperatures in the RCP scenarios, as implied by the coefficients in table 3, using the quadratic specification. Note that the estimated densities are illustrative—they interpolate across deciles using standard smoothing techniques and alternative smoothing would result in densities that differ by modest amounts (but not qualitatively).

The results highlight the quantitative magnitude of the results. The dashed lines illustrate the shift in central tendency, which is notable as previous research has emphasized (e.g., Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel, 2015; Lemoine and Kapnick 2016). The increase in the lower tail of the distribution is much more sizable—as implied by table 3. The impact of a 1°C increase in average temperature on the 10th percentile of economic growth in hot, low-income countries is near -2, so this percentile shifts down by this amount in the low emissions scenario and by nearly twice this amount in the high emissions scenario. Because the effect on the upper quantiles of growth is relatively modest, the growth distribution widens and adopts a negative skew with higher temperature. As a result, the probability of extremely poor growth outcomes—large outright declines in real GDP per capita—rises dramatically under the high and low emissions scenario.

5. Conclusions

Climate change may impact the entire distribution of economic activity over time—for example, making severe contractions in economic activity more likely with potentially sizable adverse welfare effects. The analysis herein considers the link between temperature and the percent change in real GDP per capita across the distribution of potential outcomes for 124 countries. The analysis builds on recent innovations in the application of quantile regressions in macroeconomics (the Growth at Risk literature) and in the techniques to estimate such regressions in panel data.

The results indicate substantially larger effects of temperature on downside risks to economic growth than on the central tendency of economic growth. These results suggest the growth at risk from climate change may be large. Consequently, the analysis points to a need for additional research on the effects of climate change on economic and financial stability. Moreover, the empirical results suggest a sizable increase in the likelihood of growth disasters. Given the potential welfare effects of growth disasters (e.g., Barro, 2015; Weitzman, 2014) and the role that empirical work on central tendencies has played informing damages functions in work on the social cost of carbon (e.g., Carleton and Greenstone, 2021; Rennert et al, 2021), the analysis herein suggest focus on risks to economic activity in economic damage assessments may inform work on the social cost of carbon or related policy issues.

That said, the empirical work herein does not consider the transmission mechanisms that may drive the estimated relationships. Agricultural output appears to be a key channel for growth at risk. Some previous microeconomic work on effects on central tendencies has documented the role of temperature impacting agricultural yields (Schlenker and Roberts, 2009), and microeconomic and theoretical work in this vein on risks to agricultural yields may be useful. Broader channels may also play a role and require additional research.

At the same time, empirical associations between weather and economic growth may differ from those associated with climate change, highlighting how the analysis of the links between temperature and the distribution of economic growth found herein are only one step toward understanding the effect of climate change on risks to economic growth.

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Table 1: Data Summary Statistics

	Observations	Mean	Std. Deviation	Within Country Std. Deviation
All Countries				
Percent change in real GDP per capita	5741	1.80	5.79	5.55
Temperature (C)	-	19.39	7.19	0.53
Eastern Europe and Central Asia				
Percent change in real GDP per capita	345	2.13	8.02	7.91
Temperature (C)	-	11.09	3.34	0.72
Latin America and the Caribbean				
Percent change in real GDP per capita	1216	1.61	4.66	4.58
Temperature (C)	-	22.13	4.21	0.46
Middle East and North Africa				
Percent change in real GDP per capita	438	2.06	7.36	7.11
Temperature (C)	-	20.14	4.22	0.61
Southeast Asia				
Percent change in real GDP per capita	792	2.86	4.51	4.13
Temperature (C)	-	22.12	5.23	0.36
Sub Saharan Africa				
Percent change in real GDP per capita	1751	0.95	7.25	6.97
Temperature (C)	-	23.99	3.72	0.47
Western Europe and Offshoots (e.g., United States)				
Percent change in real GDP per capita	1199	2.36	2.83	2.78
Temperature (C)	-	10.22	5.87	0.66

Figure 1: Percent Change in Real GDP Per Capita and Temperature, Annual Data, 1961-2010, Unbalanced Panel of 124 Countries.

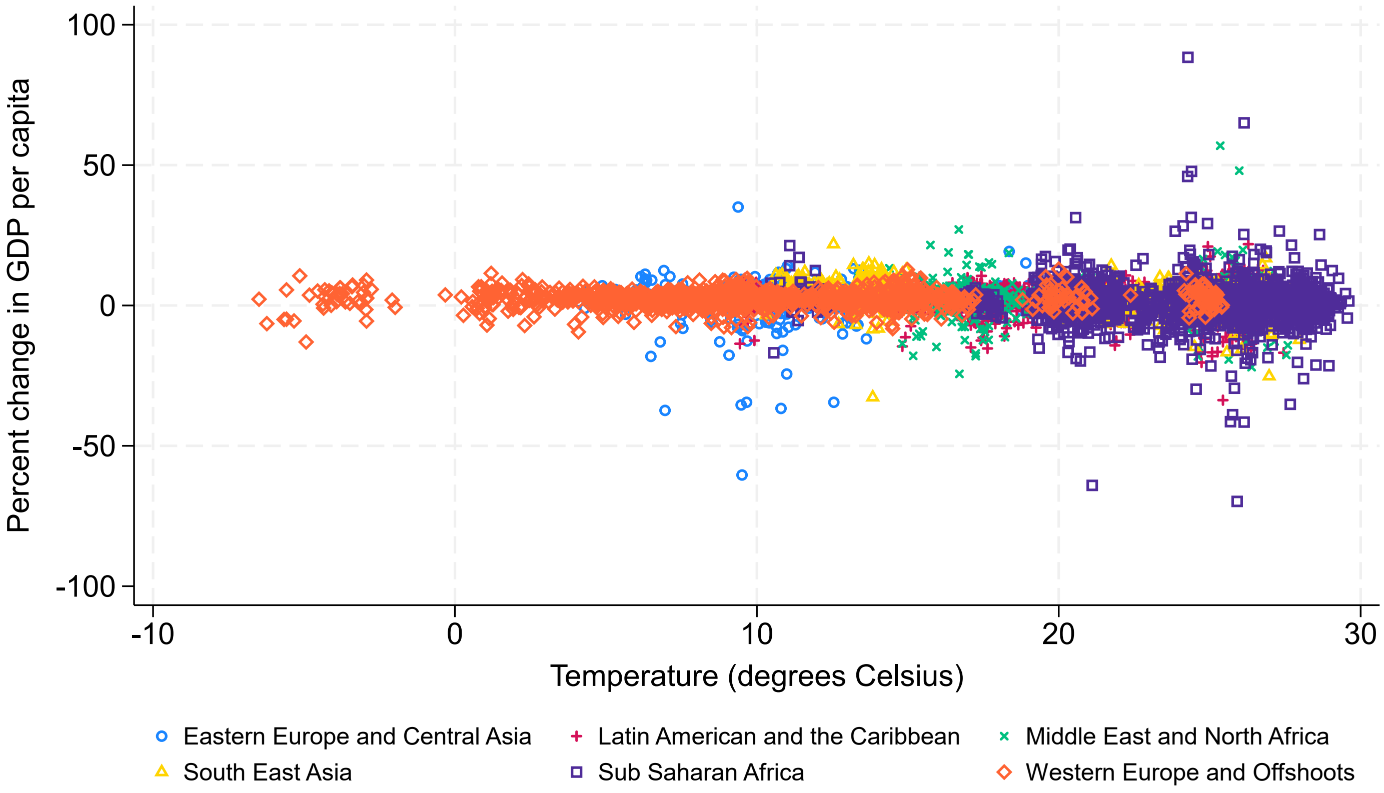


Table 2: Summary of 124 Countries Included

	Countries without outliers in the percent change of real GDP per capita	Countries with outliers in the percent change of real GDP per capita
Eastern Europe and Central Asia	Bulgaria, Romania, Turkey	Albania, Cyprus, Georgia, Hungary, Latvia, Moldova
Latin America and the Caribbean	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Guatemala, Honduras, Mexico, Peru, Paraguay, El Salvador, Trinidad and Tobago, Uruguay, Venezuela	Bahamas, Cuba, Dominican Republic, Guyana, Nicaragua, Panama, Suriname, St. Vincent and the Grenadines
Middle East and North Africa	Egypt, Morocco, *Syria*, Tunisia	United Arab Emirates, Algeria, Iran, Jordan, *Oman*, Saudi Arabia
Southeast Asia	Fiji, Indonesia, India, Japan, Korea, Sri Lanka, Malaysia, Nepal, Pakistan, Philippines, *Papua New Guinea*, Thailand, Vanuatu	Bangladesh, Brunei, Bhutan, China
Sub Saharan Africa	Benin, Burkina Faso, Central African Republic, Cameroon Congo (Rep.), Comoros, Cabo Verde, Gambia, Kenya, Mali, Mauritius, Malawi, Namibia, Sudan, Senegal, Swaziland, South Africa, Zambia	Burundi, Botswana, Cote d'Ivoire, Gabon, *Ghana, Guinea-Bissau*, *Equatorial Guinea*, Liberia, Lesotho, Madagascar, Mozambique, Mauritania, *Niger*, Nigeria, Rwanda, Sierra Leone, Chad, Togo, Congo (Dem. Rep.), Zimbabwe
Western Europe and Offshoots	Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, *Greenland, Ireland*, Iceland, *Israel*, Italy, Luxembourg, Netherlands, Norway, New Zealand, *Puerto Rico*, Portugal, Sweden, United States	

Note: Countries in *italics* are missing data on agricultural GDP and are not included in analysis of that data in tables 4 and 5. Outliers are defined as a year in which the percent change in real GDP per capita deviates from the global mean in the data sample by more than three standard deviations.

TABLE 3: BASELINE REGRESSION RESULTS $\Delta \boldsymbol{y}(\boldsymbol{t},\boldsymbol{j}) = \boldsymbol{a_j} + YEAR(t) + G(TIME(t,j)) + \boldsymbol{F}(\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j}))$.

(COLUMNS REFER TO QUANTILE REGRESSION OF THE RELATED DECILE, E.G., (5) REFERS TO 0.5 QUANTILE/MEDIAN REGRESSION)

	Least Squares	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quadratic in temperature, $\boldsymbol{F}(\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})) = \boldsymbol{a_{1,0}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j}) + \boldsymbol{a_{1,1}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})^2$										
$a_{1,0}$	0.999	1.534	1.330	1.198	1.077	0.972	0.877	0.784	0.673	0.506
	(0.386)	(0.949)	(0.720)	(0.573)	(0.457)	(0.363)	(0.292)	(0.253)	(0.259)	(0.364)
$a_{1,1}$	-0.045	-0.067	-0.059	-0.053	-0.049	-0.044	-0.040	-0.037	-0.032	-0.026
	(0.012)	(0.027)	(0.021)	(0.017)	(0.014)	(0.012)	(0.010)	(0.010)	(0.010)	(0.013)
Effect in hot countries										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.328	-1.900	-1.681	-1.540	-1.412	-1.300	-1.198	-1.098	-0.980	-0.802
Standard error	0.356	0.730	0.566	0.467	0.396	0.347	0.320	0.314	0.337	0.413
p-value	0.000	0.009	0.003	0.001	0.000	0.000	0.000	0.000	0.004	0.052
Quadratic in temperature with temperature change interactions, $\boldsymbol{F}(\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})) = \boldsymbol{a_{1,0}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j}) + \boldsymbol{a_{1,1}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})^2 + \boldsymbol{a_{2,0}}\Delta \boldsymbol{T}(\boldsymbol{t},\boldsymbol{j}) + \boldsymbol{a_{2,1}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})\Delta \boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})$										
$a_{1,0}$	0.594	0.944	0.809	0.723	0.642	0.576	0.515	0.454	0.382	0.273
	(0.606)	(1.304)	(1.004)	(0.826)	(0.691)	(0.578)	(0.495)	(0.439)	(0.418)	(0.493)
$a_{1,1}$	-0.026	-0.052	-0.042	-0.036	-0.030	-0.025	-0.020	-0.016	-0.011	-0.002
	(0.018)	(0.037)	(0.028)	(0.023)	(0.020)	(0.017)	(0.015)	(0.014)	(0.014)	(0.017)
Effect in hot countries										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-0.757	-1.745	-1.366	-1.122	-0.893	-0.706	-0.534	-0.362	-0.159	0.149
Standard error	0.436	0.936	0.708	0.580	0.488	0.423	0.388	0.384	0.415	0.521
p-value	0.083	0.062	0.054	0.053	0.067	0.095	0.169	0.345	0.702	0.775
Linear & low-income effect of Temperature, $\boldsymbol{F}(\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})) = \boldsymbol{a_{1,0}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j}) + \boldsymbol{a_{1,1}}\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})\boldsymbol{I_{low\ income}}$										
$a_{1,0}$	0.241	0.454	0.372	0.318	0.272	0.230	0.193	0.155	0.112	0.047
	(0.179)	(0.385)	(0.293)	(0.238)	(0.200)	(0.174)	(0.162)	(0.163)	(0.180)	(0.232)
$a_{1,1}$	-1.401	-2.203	-1.893	-1.691	-1.517	-1.359	-1.220	-1.078	-0.915	-0.669
	(0.481)	(1.059)	(0.819)	(0.667)	(0.552)	(0.461)	(0.395)	(0.355)	(0.353)	(0.441)
Effect in poor countries										
$a_{1,0} + a_{1,1}$	-1.160	-1.749	-1.522	-1.373	-1.245	-1.129	-1.027	-0.922	-0.803	-0.622
Standard error	0.432	1.026	0.786	0.631	0.510	0.408	0.332	0.281	0.273	0.365
p-value	0.007	0.088	0.053	0.030	0.015	0.006	0.002	0.001	0.003	0.089

Note: Data contain 5741 observations across 124 countries in the upper and bottom panel; the middle panel with interactions of the change in temperature includes 5698 observations across 124 countries. In the estimated equation, $\Delta y(t,j)$ is the percent change in real GDP per capita in period t in country j, $T(t,j)$ is average temperature in period t in country j, $I_{low\ income}$ is an indicator function equaling 1 if a country is below the median across countries in 1960, a_j are country fixed effects, $YEAR(t)$ are year fixed effects, and $G(TIME(t,j))$ are country specific linear and quadratic time trends. Standard errors obtained via the bootstrap with 200 replications, clustered by country. Finally, the effect on growth of a unit change in temperature reported in the upper and middle panel is calculated at 25.64 degrees Celsius, which it the 75th percentile for average country temperature across the 124 countries.

TABLE 4: ALTERNATIVE REGRESSIONS RESULTS, MARGINAL EFFECT IN HOT COUNTRIES $a_{1,0} + 2 * a_{1,1} * 25.64$
(COLUMNS REFER TO QUANTILE REGRESSION OF THE RELATED DECILE, E.G., (5) REFERS TO 0.5 QUANTILE/MEDIAN REGRESSION)

	Least Squares	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimates using detrended real GDP per capita										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.328	-1.900	-1.681	-1.540	-1.412	-1.300	-1.198	-1.098	-0.980	-0.802
Standard error	0.356	0.730	0.566	0.467	0.396	0.347	0.320	0.314	0.337	0.413
p-value	0.000	0.009	0.003	0.001	0.000	0.000	0.000	0.000	0.004	0.052
Estimates excluding country-specific quadratic time trends										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-0.413	-0.135	-0.246	-0.317	-0.375	-0.427	-0.475	-0.522	-0.579	-0.664
Standard error	0.294	0.528	0.403	0.341	0.306	0.292	0.296	0.315	0.354	0.438
p-value	0.160	0.799	0.542	0.352	0.221	0.144	0.108	0.098	0.102	0.129
Estimates excluding country-specific quadratic time trends and adding (post-1990 dummy)*(country fixed effects)										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.232	-1.698	-1.518	-1.400	-1.301	-1.213	-1.132	-1.050	-0.957	-0.824
Standard error	0.398	0.652	0.530	0.464	0.422	0.394	0.382	0.384	0.402	0.453
p-value	0.001	0.012	0.004	0.003	0.002	0.002	0.003	0.006	0.017	0.069
Estimates excluding country-specific quadratic time trends, only post-1990 data										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.071	-1.807	-1.524	-1.345	-1.195	-1.049	-0.924	-0.803	-0.671	-0.513
Standard error	0.762	1.223	1.008	0.891	0.816	0.759	0.722	0.703	0.699	0.728
p-value	0.121	0.179	0.131	0.131	0.143	0.167	0.201	0.253	0.338	0.481
Estimates using growth in agricultural real GDP per capita										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-2.685	-4.456	-3.798	-3.369	-2.997	-2.660	-2.352	-1.999	-1.574	-0.921
Standard error	0.724	1.144	0.945	0.841	0.770	0.723	0.700	0.705	0.744	0.877
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.005	0.034	0.294
Estimates using growth in nonagricultural real GDP per capita										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-0.933	-0.608	-0.736	-0.819	-0.884	-0.946	-1.003	-1.064	-1.130	-1.237
Standard error	0.586	1.031	0.780	0.661	0.603	0.588	0.618	0.683	0.788	1.008
p-value	0.111	0.556	0.345	0.215	0.142	0.108	0.104	0.119	0.151	0.220

Note: See notes to table 3 for variable definitions. Standard errors obtained via the bootstrap with 200 replications, clustered by country. The effect on growth of a unit change in temperature reported in is calculated at 25.64 degrees Celsius, which it the 75th percentile for average country temperature across the 124 countries.

TABLE 5: SENSITIVITY OF REGRESSION RESULTS TO OUTLIERS $\Delta \boldsymbol{y}(\boldsymbol{t},\boldsymbol{j}) = \boldsymbol{a_j} + YEAR(t) + G(TIME(t,j)) + \boldsymbol{a_{1,0}T(t,j)} + \boldsymbol{a_{1,1}T(t,j)}^2$.

(COLUMNS REFER TO QUANTILE REGRESSION OF THE RELATED DECILE, E.G., (5) REFERS TO 0.5 QUANTILE/MEDIAN REGRESSION)

	Least Squares	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Previously reported baseline results for all countries from table 3 (real GDP per capita) and table 4 (agricultural GDP)										
Effect in hot countries on percent change in real GDP										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.328	-1.900	-1.681	-1.540	-1.412	-1.300	-1.198	-1.098	-0.980	-0.802
Standard error	0.356	0.730	0.566	0.467	0.396	0.347	0.320	0.314	0.337	0.413
p-value	0.000	0.009	0.003	0.001	0.000	0.000	0.000	0.000	0.004	0.052
Effect in hot countries on percent change in agricultural GDP										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-2.685	-4.456	-3.798	-3.369	-2.997	-2.660	-2.352	-1.999	-1.574	-0.921
Standard error	0.724	1.144	0.945	0.841	0.770	0.723	0.700	0.705	0.744	0.877
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.005	0.034	0.294
Results deleting countries with outliers (deletions shown in table 2)										
Effect in hot countries on percent change in real GDP										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.158	-1.985	-1.682	-1.467	-1.283	-1.110	-0.971	-0.822	-0.651	-0.402
Standard error	0.341	0.592	0.481	0.413	0.366	0.334	0.319	0.314	0.328	0.372
p-value	0.001	0.001	0.000	0.000	0.000	0.001	0.002	0.009	0.047	0.279
Effect in hot countries on percent change in agricultural GDP										
$a_{1,0} + 2 * a_{1,1} * 25.64$	-2.714	-3.521	-3.223	-3.022	-2.860	-2.705	-2.549	-2.392	-2.194	-1.921
Standard error	0.643	0.972	0.800	0.709	0.661	0.646	0.656	0.694	0.770	0.931
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.004	0.039
Results with standardized growth (real GDP or agricultural GDP), where impact in hot country is based on global within-country standard deviation of growth in real GDP per capita (equal to 5.79 percentage points) or of growth in agricultural GDP per capita (equal to 8.83 percentage points)										
Effect in hot countries on percent change in real GDP										
$(a_{1,0} + 2 * a_{1,1} * 25.64) * 5.79$	-1.453	-2.212	-1.916	-1.714	-1.552	-1.401	-1.280	-1.152	-1.002	-0.776
Standard error	0.347	0.677	0.533	0.446	0.382	0.336	0.318	0.307	0.324	0.382
p-value	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.043
Effect in hot countries on percent change in agricultural GDP										
$(a_{1,0} + 2 * a_{1,1} * 25.64) * 8.83$	-2.817	-4.309	-3.753	-3.391	-3.091	-2.790	-2.508	-2.199	-1.863	-1.316
Standard error	0.627	1.015	0.839	0.742	0.680	0.627	0.609	0.609	0.653	0.768
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.087

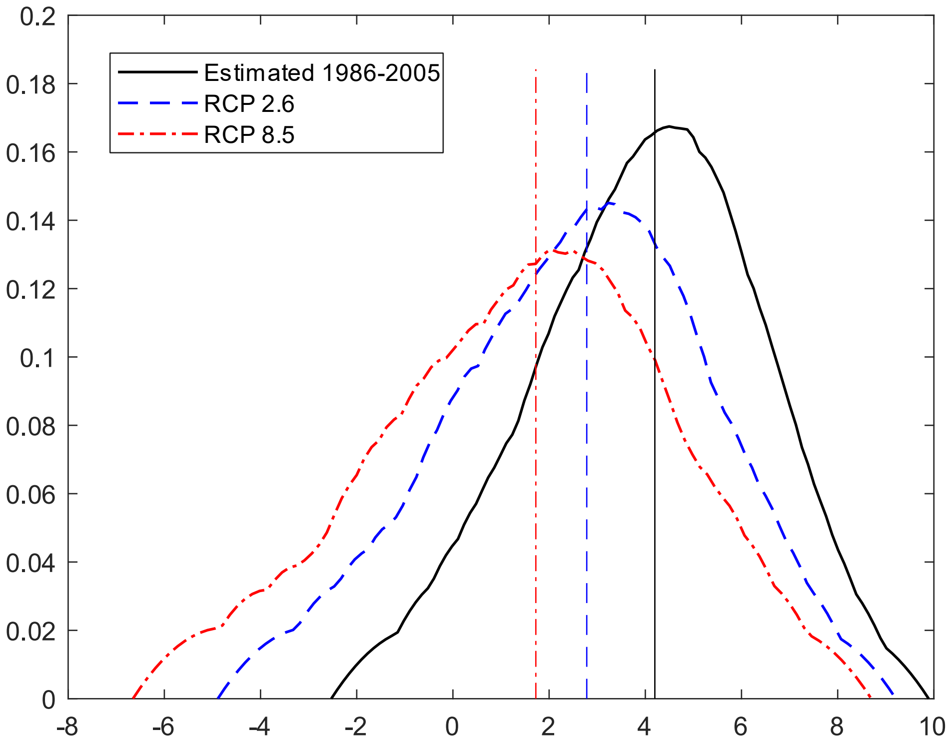
Note: See notes to table 3 for variable definitions. Standard errors obtained via the bootstrap with 200 replications, clustered by country. The effect on growth of a unit change in temperature reported in is calculated at 25.64 degrees Celsius, which it the 75th percentile for average country temperature across the 124 countries.

Table 6: Impacts on Distribution of Percent Change in Real GDP per Capita Across Selected Countries

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
			10th percentile		**Median**		**90th percentile**	
Country	**Ave. Temp. 1986-2005**	**ΔTemp., RCP 8.5**	**Marginal impact**	**Impact= ΔT*Marg. impact**	**Marginal impact**	**Impact= ΔT*Marg. impact**	**Marginal impact**	**Impact= ΔT*Marg. impact**
USA	13.69	2.57						
Quadratic specification			-0.30	-0.77	-0.23	-0.60	-0.21	-0.53
Linear/low-income specification			0.45	1.17	0.23	0.59	0.05	0.12
Brazil	22.25	2.08						
Quadratic specification			-1.45	-3.00	-0.99	-2.05	-0.65	-1.35
Linear/low-income specification			0.45	0.94	0.23	0.48	0.05	0.10
India	25.64	1.93						
Quadratic specification			-1.90	-3.66	-1.28	-2.47	-0.83	-1.59
Linear/low-income specification			-1.75	-3.37	-1.13	-2.17	-0.62	-1.20
Nigeria	26.77	1.88						
Quadratic specification			-2.05	-3.87	-1.38	-2.61	-0.89	-1.67
Linear/low-income specification			-1.75	-3.30	-1.13	-2.13	-0.62	-1.17

Note: Average temperature measured in °C. The United States and Brazil have average incomes that exceed the median across countries (and hence are high-income countries) and India and Nigeria have average incomes that fall below the median (and hence are low-income countries). The marginal impacts are constant across high or low incomes in the linear specification.

Figure 2: Effects of Alternative Representative Concentration Pathways on the Probability Distribution Function (PDF) of the Percent Change in Real GDP Per Capita in India



Source: Author's calculations based on results in table 3 using quadratic specification (augmented to include the 19 quantiles spanning from 0.05 to 0.95, in 0.05 increments). Vertical lines indicate medians.