Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

Growth at Risk From Climate Change

Michael T. Kiley

2021-054

Please cite this paper as:
Kiley, Michael T. (2021). "Growth at Risk From Climate Change," Finance and Economics Discussion Series 2021-054. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2021.054.

Growth at Risk From Climate Change

Michael T. Kiley[*]

Version 7

July 24, 2021

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.

JEL codes: E23, O13, Q54, Q56

Keywords: Climate change, Risk management, GDP at Risk

---

[*] Federal Reserve Board, Washington DC. Email: mkiley@frb.gov. Michael Kiley is Deputy Director of the Division of Financial Stability of the Federal Reserve Board. The views expressed herein are those of the author, and do not reflect those of the Federal Reserve Board or its staff. This research has benefited from code supplied by Joao M.C. Santos Silva, a Federal Reserve Board workshop, and comments from Marshall Burke, Solomon Hsiang, Brigitte Roth Tran, Joao M.C. Santos Silva, and Daniel Wilson.

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).

A risk associated with climate change is potentially greater variability or 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), but typical scenario analysis considers adverse tail outcomes and existing empirical work does not link climate change to tail risks to economic activity.[1]

This risk is explored using quantile regressions, as in the literature on Growth at Risk (e.g., IMF, 2017; Adrian, Boyarchenko, and Giannone, 2019; and Kiley, forthcoming). 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 significant 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 below for India. The results highlight the need to assess the impact of climate change on economic fluctuations, especially fluctuations leading to severe economic contractions.

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, and Nordhaus (2011) highlights the importance of correlations between

[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).

adverse climate and macroeconomic outcomes in assessing welfare impacts of climate change in an integrated assessment model.[2]

A focus on tail outcomes is not typical in macroeconomics, and the analysis herein builds on research using quantile regressions to consider tail risks following IMF (2017), Adrian, Boyarchenko, and Giannone (2019), and Kiley (forthcoming). The approach herein that links growth and temperature to assess the possible effects associated with climate change has been used elsewhere (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; and Kalkuhl and Wenz (2020)). The advantages and disadvantages of this approach have been explored (Dell, Jones, and Olken, 2014; Hsiang, 2016; Lemoine, 2021b) and are briefly discussed below; Carleton and Greenstone (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.

While the research on the effects of climate change on economic growth has not explored effects on tail outcomes (a missing link emphasized by the NGFS in Bertram et al, 2021), 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.

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 concludes.

2. Data and approach

2.1 Data

Our approach extends the analysis of Dell, Jones, and Olken (2012a), Burke, Hsiang, and Miguel (2015), Burke, Davis, and Diffenbaugh (2018), and Kalkuhl and Wenz (2020) 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).[3] 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

[2] A related focus on extreme outcomes is research on macroeconomic fluctuations and violent conflict. For example, deep economic contractions have been shown to increase the risk of violent conflict (Collier and Hoeffler, 2004; Collier, Hoeffler, and Rohner, 2009; Kim and Conceição, 2010).

[3] An early version of this research used data from the replication codes of Dell, Jones, and Olken, 2012b. Despite some differences in country coverage and time period, the results were very similar across datasets.

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 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) and 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—the within country standard deviations are relatively small compared to between country differences. At the same time, the standard deviation of temperature within country from year-to-year is sizable, on the order of 0.5-0.7 degrees Celsius, which highlights how large year-to-year movements in temperature observed in the data are similar in magnitude to the anticipated increase in temperature associated with climate change in coming decades (as discussed briefly below).

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 Zth conditional percentile is

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

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) $$\Delta y(t,j) = a_j + A_D D + F\big(T(t,j)\big).$$

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 ($A_D D$), a vector of quadratic country-specific time trends and year dummy variables.

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. 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 specification 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, 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).

At the same time, 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 not widely employed. The approach herein follows the quantiles-via-moments method of Machado and Santos Silva, 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, forthcoming). 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 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 wight on a subset of observations in the neighborhood of the quantile of interest more heavily, while weighting other observations less heavily—which is akin to a reduction in sample size.

To set baseline results, table 2 reports results for equation 2 using least squares and median (least absolute deviations, Z equal to the 50th percentile) regression for the first and third specification of $F\big(T(t,j)\big)$, as a preview to the quantile regression analysis. 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 and on economic growth. In particular, the adverse impact on economic growth is confined to hot countries (columns 1 and 2, upper panel) or poor countries (columns 3 and 4)—with the central tendency of growth falling about 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. All told, the results suggest that a quadratic or linear specification is not central for assessing the nature of the effect—a result that will be echoed below. That said, the linear and quadratic specifications have drastically different implications under some scenarios. Related work must be careful to assess the nature of underlying empirical relationships in light of the question such work addresses.

3. Temperature and Growth at Risk

3.1 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 1 and the 90th in column 9. The upper rows report results using baseline quadratic specification, and the 5th column repeats the median regression from table 2, column 2.

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.

3.2 Robustness checks

A variety of robustness checks were considered, the most important of which consider variations on the functional form of the relationship between temperature and growth reported in the remaining rows of table 3. The qualitative and quantitative results are broadly similar—downside risks to economic growth are much more strongly linked to temperature than upside risks.

Allowing for effects of the short-run change in temperature weakens the link between temperature and growth—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 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, albeit lower levels than in the main quadratic specification.

These results point to several takeaways. First, the results in the literature on average relationships (e.g., Dell, Jones, and Olken, 2012; Burke, Hsiang, and Solomon, 2015) may understate the degree to which an increase in temperature associated with climate change may lead to adverse effects on economic activity. The quantile regressions highlight how climate change may increase the risk of very poor growth outcomes—which 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). Second and relatedly, 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. This points to the importance of considering the impact of climate change on economic stability (e.g., Litterman, 2020; Giglio, Kelly, and Stroebel, 2020; Bertram et al, 2021). 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—for example, because of adaptations on the part of households, businesses, and governments.[4]

3.3 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. (Note that examples for Eastern Europe and Central Asia and for the Middle East and North Africa are not shown, in part because results are not different and in part because the large countries of these regions—Russia and Egypt—are not within the sample of countries in the data.)

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 4 presents results. The United States is a relatively temperate country. As a result, the impact on the 10^{th} percentile, median, and 90^{th} 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) and the main result is that the effect is modest relative to that on other countries for the United States and similar countries.

[4] One concern with extrapolating results in the regressions to the future is that adaptations may result in a lower effect of temperature in the future as time passes and adaptation occurs. The specification with interactions for the change in temperature (from Kalkuhl and Wenz, 2020) point to more modest effects of temperature on the median and upper quantiles of the distribution for the percent change in real GDP per capita. Note these results still demonstrate the sharp asymmetry that is the key result, with sizable impacts of temperature on downside risks to growth.

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; 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]

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: That is, the distribution of economic growth shifts down and the downside risk increases sizably.

The effect on the distribution can be illustrated by presenting probability density functions implied by the quantile regression results. Figure 1 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 9 deciles 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 imply 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 imply 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] 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 deciles 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

[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/ .

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 to a sizable degree with climate change. As a result, the probability of extremely poor growth outcomes—large outright declines in real GDP per capita—rises dramatically under the high emissions scenario (and even under the low emissions scenario).

3.3 Caveats

The empirical link between temperature and the distribution of economic growth in hot or low-income countries is strong, highlighting how growth at risk from climate change may be notably greater than results focused on central tendencies may have appreciated. At the same time, extrapolating the results to the potential impact of climate change, as in figure 1, may be inappropriate because the empirical relationship is based on year-to-year fluctuations of temperature in a country. This approach has the advantage of eliminating country-specific factors that may account for the negative relationship between income and temperature highlighted above (i.e., the debate between Acemoglu, Johnson, and Robinson, 2002, and Sachs, 2003). At the same time, 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. Note that research has attempted to account for the role of adaptations in their analysis by considering long differences in real GDP per capita—that is, decade or multidecade growth periods over which adaptation may have occurred in the past, potentially hinting at the possibility of future adaptations. As the study herein is focused on the risk of large declines in real GDP within a year, this approach is not useful in the current context.

4. 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 and support additional research on the effects of climate change on economic and financial stability. 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.

References

Acemoglu, Daron, Simon Johnson, and James A. Robinson. 2002. “Reversal of Fortune: Geography and Institutions in the Making of the Modern World Income Distribution.” Quarterly Journal of Economics 117 (4): 1231–94.

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." American Economic Review, 109 (4): 1263-89. DOI: 10.1257/aer.20161923

Robert J. Barro, 2015. "Environmental Protection, Rare Disasters and Discount Rates," Economica, London School of Economics and Political Science, vol. 82(325), pages 1-23, January.

Bertram, Christoph et al. 2021. NGFS Climate Scenario Database: Technical Documentation V2.2. https://www.ngfs.net/sites/default/files/ngfs_climate_scenarios_technical_documentation__phase2_june2021.pdf.

Burke, M, SM Hsiang, E Miguel (2015). Global Non-linear Effect of Temperature on Economic Production. Nature 527: 235-239.

Burke, M., M. Davis, N. Diffenbaugh. 2018. "Large potential reduction in economic damages under UN mitigation targets", Nature, 557, 549-553

Canay, I.A. (2011). A Simple Approach to Quantile Regression for Panel Data, Econometrics Journal, 14, 368-386.

Carleton, Tamma and Michael Greenstone, 2021. Updating the United States Government’s Social Cost of Carbon. Energy Policy Institute at the University of Chicago WORKING PAPER · NO. 2021-04, JANUARY 2021.

Cecchetti, Stephen G. and Hong Li. 2008, “Measuring the Impact of Asset Price Booms Using Quantile Vector Autoregressions,” unpublished manuscript, Brandeis International Business School.

Clark, Pilita (2021) The future of work is already here and it is seriously hot. The Financial Times. July 4. https://www.ft.com/content/1b6b61aa-eb9e-4f19-bad1-ca04ba6d8935?shareType=nongift.

Collier, Paul and Anke Hoeffler. 2004. "Greed and Grievance in Civil War." Oxford Economic Papers, Vol. 56, Issue 4, pp. 563-95.

Collier, Paul, Anke Hoeffler, and Dominic Rohner. 2009. "Beyond Greed and Grievance: Feasibility and Civil War." Oxford Economic Papers, Vol. 61, Issue 1, pp. 1-27.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2009. “Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates.” American Economic Review 99 (2): 198–204.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012a. “Temperature Shocks and Economic Growth: Evidence from the Last Half Century.” American Economic Journal: Macroeconomics.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012b. “Temperature Shocks and Economic Growth: Evidence from the Last Half Century: Dataset.” American Economic Journal: Macroeconomic.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." Journal of Economic Literature, 52 (3): 740-98.

Deschenes, Olivier, and Michael Greenstone. 2007. “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather.” American Economic Review 97 (1): 354–85.

Gallup, John Luke, Jeffrey D. Sachs, and Andrew D. Mellinger. 1999. “Geography and Economic Development.” International Regional Science Review 22 (2): 179–232.

Hocking C, Silberstein RB, Lau WM, Stough C, Roberts W. 2001. Evaluation of cognitive performance in the heat by functional brain imaging and psychometric testing. Comp. Biochem. Physiol. A128:719–34

Hsiang, Solomon. 2016. Climate Econometrics. Annual Review of Resource Economics 8:1, 43-75

IMF. 2017. Financial Conditions and Growth at Risk, Global Financial Stability Report, October, Chapter 3.

Kato, K., Galvao, A.F. and Montes-Rojas, G. (2012). Asymptotics for Panel Quantile Regression Models with Individual Effects, Journal of Econometrics, 170, 76-91.

Kiley, Michael T. forthcoming. "Unemployment Risk," Journal of Money, Credit, and Banking.

Kim, Namsuk and Pedro Conceição, 2010),The Economic Crisis, Violent Conflict, and Human Development. International Journal of Peace Studies, Volume 15, Number 1, Spring/Summer 2010

Koenker, Roger and Kevin F. Hallock. 2001. “Quantile Regression,” Journal of Economic Perspectives 15(4): 143-156.

Lemoine, D., Kapnick, S. A top-down approach to projecting market impacts of climate change. Nature Clim Change 6, 51–55 (2016). https://doi.org/10.1038/nclimate2759

Lemoine, Derek. 2021a. "The climate risk premium: how uncertainty affects the social cost of carbon." Journal of the Association of Environmental and Resource Economists 8, no. 1 : 27-57.

Lemoine, D. 2021b. 'Estimating the Consequences of Climate Change from Variation in Weather'. London, Centre for Economic Policy Research. https://cepr.org/active/publications/discussion_papers/dp.php?dpno=16194

Litterman, Robert (2020) Managing Climate Risk in the U.S. Financial System. Harvard Law School Forum on Corporate Governance, October 1. https://corpgov.law.harvard.edu/2020/10/01/managing-climate-risk-in-the-u-s-financial-system/.

Machado, J.A.F. and Santos Silva, J.M.C. (2019), Quantiles via Moments, Journal of Econometrics, forthcoming.

Montesquieu, Charles de Secondat. 1750. The Spirit of Laws. London: J. Nourse and P. Vaillant.

Nordhaus, W. 2011. Estimates of the social cost of carbon: Background and results from the RICE-2011 model, Working Paper 17540, National Bureau of Economic Research.

Sachs, Jeffrey D. 2003. Institutions Don't Rule: Direct Effects of Geography on Per Capita Income. Cambridge, Mass. National Bureau of Economic Research. NBER working paper no. w9490, February.

Sachs, Jeffrey D., and Andrew M. Warner. 1997. "Sources of Slow Growth in African Economies." Journal of African Economies 6 (3): 335–7

Martin L. Weitzman, 2014. "Fat Tails and the Social Cost of Carbon," American Economic Review, American Economic Association, vol. 104(5), pages 544-546, May.

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 American 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
South East 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

TABLE 2: REGRESSIONS FOR EFFECTS ON CENTRAL TENDENCY

$$\Delta \boldsymbol{y}(\boldsymbol{t},\boldsymbol{j}) = \boldsymbol{a}_{\boldsymbol{j}} + \boldsymbol{A}_{\boldsymbol{D}}\boldsymbol{D} + \boldsymbol{F}\big(\boldsymbol{T}(\boldsymbol{t},\boldsymbol{j})\big).$$

	QUADRATIC IN TEMPERATURE $F(T(t,j)) = a_{1,0}T(t,j) + a_{1,1}T(t,j)^2$		LINEAR & LOW-INCOME EFFECT OF TEMPERATURE $F(T(t,j)) = a_{1,0}T(t,j) + a_{1,1}T(t,j)I_{low\ income}$	
	Least squares regression (1)	**Median regression (2)**	**Least squares regression (3)**	**Median regression (4)**
$a_{1,0}$	0.999	0.972	0.241	0.230
	(0.386)	(0.363)	(0.179)	(0.174)
$a_{1,1}$	-.045	-0.044	-1.401	-1.359
	(0.012)	(0.012)	(0.481)	(0.461)
Observations	5,741	5,741	5,741	5,741
Number of countries	124	124	124	124
TEMPERATURE EFFECT IN HOT COUNTRIES, $\frac{dF}{dT}_{T=25.64} = a_{1,0} + 2 * a_{1,1} * 25.64$				
Effect	-1.328	-1.300		
Standard error	0.356	0.347		
p-value	0.000	0.000		
TEMPERATURE EFFECT IN LOW-INCOME COUNTRIES, $\frac{dF}{dT}_{I_{low\ income}=1} = a_{1,0} + a_{1,1}$				
Effect			-1.160	-1.129
Standard error			0.432	0.408
p-value			0.007	0.006

Note: $\Delta y(t,j)$ 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 and $A_D D$ are country specific linear and quadratic time trends with year fixed effects. Standard errors in parentheses obtained via the bootstrap with 200 replications, clustered by country.

TABLE 3: QUANTILE REGRESSIONS $\Delta y(t,j) = a_j + A_D D + F(T(t,j))$.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quadratic in temperature, $F(T(t,j)) = a_{1,0}T(t,j) + a_{1,1}T(t,j)^2$									
$a_{1,0}$	1.534	1.330	1.198	1.077	0.972	0.877	0.784	0.673	0.506
	(0.949)	(0.720)	(0.573)	(0.457)	(0.363)	(0.292)	(0.253)	(0.259)	(0.364)
$a_{1,1}$	-0.067	-0.059	-0.053	-0.049	-0.044	-0.040	-0.037	-0.032	-0.026
	(0.027)	(0.021)	(0.017)	(0.014)	(0.012)	(0.010)	(0.010)	(0.010)	(0.013)
Effect in hot countries									
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.900	-1.681	-1.540	-1.412	-1.300	-1.198	-1.098	-0.980	-0.802
Standard error	0.730	0.566	0.467	0.396	0.347	0.320	0.314	0.337	0.413
p-value	0.012	0.003	0.001	0.000	0.000	0.000	0.000	0.004	0.052
Quadratic in temperature with temperature change interactions, $F(T(t,j)) = a_{1,0}T(t,j) + a_{1,1}T(t,j)^2 + a_{2,0}\Delta T(t,j) + a_{2,1}T(t,j)\Delta T(t,j)$									
$a_{1,0}$	0.944	0.809	0.723	0.642	0.576	0.515	0.454	0.382	0.273
	(1.281)	(1.004)	(0.826)	(0.691)	(0.578)	(0.495)	(0.439)	(0.418)	(0.493)
$a_{1,1}$	-0.052	-0.042	-0.036	-0.030	-0.025	-0.020	-0.016	-0.011	-0.002
	(0.036)	(0.028)	(0.023)	(0.020)	(0.017)	(0.015)	(0.014)	(0.014)	(0.017)
Effect in hot countries									
$a_{1,0} + 2 * a_{1,1} * 25.64$	-1.745	-1.366	-1.122	-0.893	-0.706	-0.534	-0.362	-0.159	0.149
Standard error	0.941	0.708	0.580	0.488	0.423	0.388	0.384	0.415	0.521
p-value	0.064	0.054	0.053	0.067	0.095	0.169	0.345	0.702	0.775
Linear & low-income effect of Temperature, $F(T(t,j)) = a_{1,0}T(t,j) + a_{1,1}T(t,j)I_{low\ income}$									
$a_{1,0}$	0.454	0.372	0.318	0.272	0.230	0.193	0.155	0.112	0.047
	(0.385)	(0.293)	(0.238)	(0.200)	(0.174)	(0.162)	(0.163)	(0.180)	(0.232)
$a_{1,1}$	-2.203	-1.893	-1.691	-1.517	-1.359	-1.220	-1.078	-0.915	-0.669
	(1.059)	(0.819)	(0.667)	(0.552)	(0.461)	(0.395)	(0.355)	(0.353)	(0.441)
Effect in poor countries									
$a_{1,0} + a_{1,1}$	-1.749	-1.522	-1.373	-1.245	-1.129	-1.027	-0.922	-0.803	-0.622
Standard error	1.026	0.786	0.631	0.510	0.408	0.332	0.281	0.273	0.365
p-value	0.088	0.053	0.030	0.015	0.006	0.002	0.001	0.003	0.089

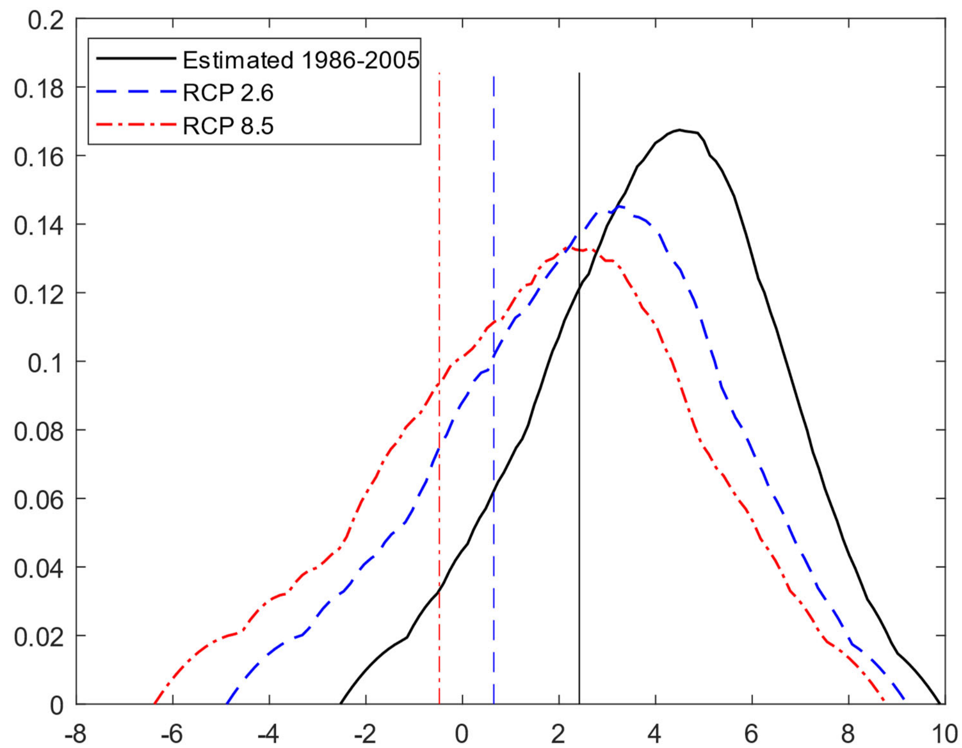
Note: Data contain 5741 observations across 124 countries in the upper and bottom panel; the middle panel with interactions of the change in temperature includes 5698 observations across 124 countries. $\Delta y(t,j)$ is the percent change in real GDP per capita in period t in country j, $T(t,j)$ is 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 and $A_D D$, are country specific linear and quadratic time trends with year fixed effects. Standard errors in parentheses obtained via the bootstrap with 200 replications, clustered by country.

Table 4: 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**	**Margina l impact**	**Impact= ΔT*Marg. impact**	**Marginal impact**	**Impact= ΔT*Marg. impact**
USA	13.69	2.51						
Quadratic specification			-0.30	-0.75	-0.24	-0.60	-0.19	-0.48
Linear/low income specification			0.45	1.14	0.23	0.58	0.05	0.12
Brazil	22.25	1.97						
Quadratic specification			-1.45	-2.85	-1.00	-1.97	-0.63	-1.24
Linear/low income specification			0.45	0.89	0.23	0.45	0.05	0.09
India	25.64	1.89						
Quadratic specification			-1.90	-3.59	-1.30	-2.46	-0.80	-1.52
Linear/low income specification			-1.75	-3.31	-1.13	-2.13	-0.62	-1.17
Nigeria	26.77	1.81						
Quadratic specification			-2.05	-3.71	-1.40	-2.53	-0.86	-1.56
Linear/low income specification			-1.75	-3.17	-1.13	-2.04	-0.62	-1.13

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 1: 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.