



# Global warming has increased global economic inequality

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**Understanding the causes of economic inequality is critical for achieving equitable economic development. To investigate whether global warming has affected the recent evolution of inequality, we combine counterfactual historical temperature trajectories from a suite of global climate models with extensively replicated empirical evidence of the relationship between historical temperature fluctuations and economic growth. Together, these allow us to generate probabilistic country-level estimates of the influence of anthropogenic climate forcing on historical economic output. We find very high likelihood that anthropogenic climate forcing has increased economic inequality between countries. For example, per capita gross domestic product (GDP) has been reduced 17–31% at the poorest four deciles of the population-weighted country-level per capita GDP distribution, yielding a ratio between the top and bottom deciles that is 25% larger than in a world without global warming. As a result, although between-country inequality has decreased over the past half century, there is ~90% likelihood that global warming has slowed that decrease. The primary driver is the parabolic relationship between temperature and economic growth, with warming increasing growth in cool countries and decreasing growth in warm countries. Although there is uncertainty in whether historical warming has benefited some temperate, rich countries, for most poor countries there is >90% likelihood that per capita GDP is lower today than if global warming had not occurred. Thus, our results show that, in addition to not sharing equally in the direct benefits of fossil fuel use, many poor countries have been significantly harmed by the warming arising from wealthy countries' energy consumption.**

economic inequality | global warming | climate change attribution | CMIP5

**D**etection of impacts caused by historical global warming has increased substantially in the past decade, including documented impacts on agriculture, human health, and ecosystems (1). Quantifying these historical impacts is critical for understanding the costs and benefits of global warming, and for designing and evaluating climate mitigation and adaptation measures (1).

The impact of historical warming on economic inequality is of particular concern (2). There is growing evidence that poorer countries or individuals are more negatively affected by a changing climate, either because they lack the resources for climate protection (3) or because they tend to reside in warmer regions where additional warming would be detrimental to both productivity and health (4–6). Furthermore, given that wealthy countries have been responsible for the vast majority of historical greenhouse gas emissions, any clear evidence of inequality in the impacts of the associated climate change raises critical questions of international justice.

More broadly, measuring and understanding the past and present evolution of global economic inequality is an area of active research and policy interest, with ongoing disagreement about the nature and causes of observed inequality trends (7–10). Quantifying any climatic influence on these trends thus has implications beyond climate risk management.

Recent research has identified pathways by which changes in climate can affect the fundamental building blocks of economic production (11, 12). Empirical work has included sector-specific

analyses of agriculture, labor productivity, and human health (12), as well as analyses of aggregate indicators such as gross domestic product (GDP) (4, 13). A key insight is the nonlinear response of many outcomes to temperature change, with the coolest regions often benefitting in warm years, and warmer regions being harmed. As a result, empirical evidence combined with projections of future climate change suggests that, although some wealthy countries in cooler regions could benefit from additional warming, most poor countries are likely to suffer (4, 14).

Efforts to apply empirical approaches to explicitly quantify the spatial pattern of aggregate impacts have primarily focused on future climate change (4–6, 14), with quantification of historical impacts being limited to specific economic sectors and outcomes (e.g., ref. 1), or to global GDP (12). Likewise, although a number of researchers have noted that the most robust regional warming has generally occurred in lower-latitude regions that are currently relatively poor (e.g., refs. 15–19), these analyses have not attempted to quantify the distributional impacts of historical temperature change.

Here, we build on past work linking economic growth and fluctuations in temperature (4, 14) to quantify the impact of historical anthropogenic climate forcing on the global distribution of country-level per capita GDP (*Materials and Methods* and Fig. 1). We use the Historical and Natural climate model simulations from the Coupled Model Intercomparison Project (CMIP5) (20) to quantify the temperature trajectory of different countries in the absence of anthropogenic forcing. We then combine these counterfactual country-level temperature trajectories

## Significance

**We find that global warming has very likely exacerbated global economic inequality, including ~25% increase in population-weighted between-country inequality over the past half century. This increase results from the impact of warming on annual economic growth, which over the course of decades has accumulated robust and substantial declines in economic output in hotter, poorer countries—and increases in many cooler, wealthier countries—relative to a world without anthropogenic warming. Thus, the global warming caused by fossil fuel use has likely exacerbated the economic inequality associated with historical disparities in energy consumption. Our results suggest that low-carbon energy sources have the potential to provide a substantial secondary development benefit, in addition to the primary benefits of increased energy access.**

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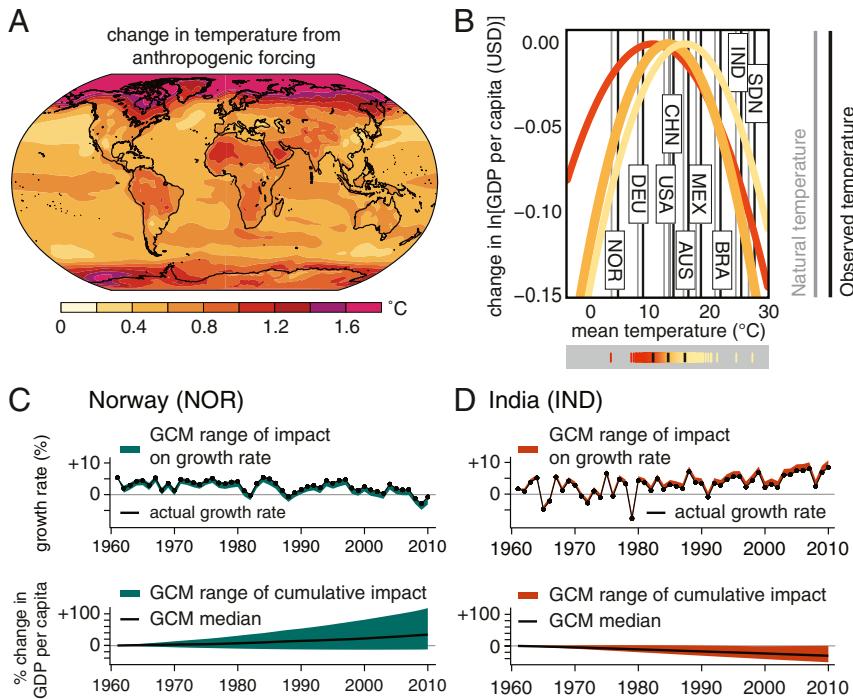
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## Quantifying the country-level economic impact of historical global warming



**Fig. 1.** Response of temperature and per capita GDP to global warming. (A) The ensemble-mean difference in annual temperature between the CMIP5 Historical and Natural forcing experiments during the IPCC's historical baseline period (1986–2005). (B) The annual temperature for selected countries from historical observations [black; calculated as in Burke et al. (14)] and the world without anthropogenic climate forcing (gray). Overlaid on the country-level temperatures are the response functions containing the 10th (red), 50th (orange), and 90th (yellow) percentile temperature optima, calculated across the 1,000 temperature optima generated by the bootstrap replication of the regression. The full distribution of temperature optima from ref. 14 is shown in the gray box; as in ref. 14, darker red colors indicate cooler temperature optima and thus greater likelihood of negative impacts from warming. (C and D) The impact of anthropogenic climate forcing on annual economic growth rate, and accumulated impact on per capita GDP, for Norway and India.

with empirically derived nonlinear temperature–GDP response functions to calculate the counterfactual per capita GDP of individual countries over the past half century. Finally, we use those counterfactual country-level economic trajectories to calculate the impact of historical anthropogenic forcing on population-weighted country-level economic inequality, accounting for both uncertainty in the relationship between temperature and economic growth and uncertainty in the climate response to historical forcing.

### Results

The estimated parabolic relationship between temperature and economic growth means that long-term warming will generally increase growth in cool countries and decrease growth in warm countries (Fig. 1). For example, for cooler countries such as Norway, warming moves the country-mean temperature closer to the empirical optimum (Fig. 1B), resulting in cumulative economic benefits (Fig. 1C). In contrast, for warm countries such as India, warming moves the country-mean temperature further from the optimum (Fig. 1B), resulting in cumulative losses (Fig. 1D).

As a result, anthropogenic climate forcing has decreased economic growth of countries in the low latitudes and increased economic growth of countries in the high latitudes (Fig. 2). The median losses exceed 25% for the 1961–2010 period (relative to a world without anthropogenic forcing) over large swaths of the tropics and subtropics (Fig. 2A), where most countries exhibit very high likelihood of negative impacts (Fig. 2C and D), including >99% likelihood (*SI Appendix*, Table S1). The median gains can be at least as large in the high latitudes, where many countries exhibit >90% likelihood of positive impacts. Many countries in the middle latitudes exhibit median impacts smaller than  $\pm 10\%$ , along with greater uncertainty in the sign of the response (particularly in the northern hemisphere). Thus, the global-scale pattern is of cool countries benefitting and warm countries suffering, with temperate countries exhibiting the greatest uncertainty.

Although this global pattern could be expected from the concave structure of the empirical temperature–growth relationship (Fig. 1B), such an outcome is not determined for historical climate forcing, because internal climate variability creates uncertainty in the sign and magnitude of regional temperature change (e.g., refs. 21 and 22). However, because the mean temperature response is

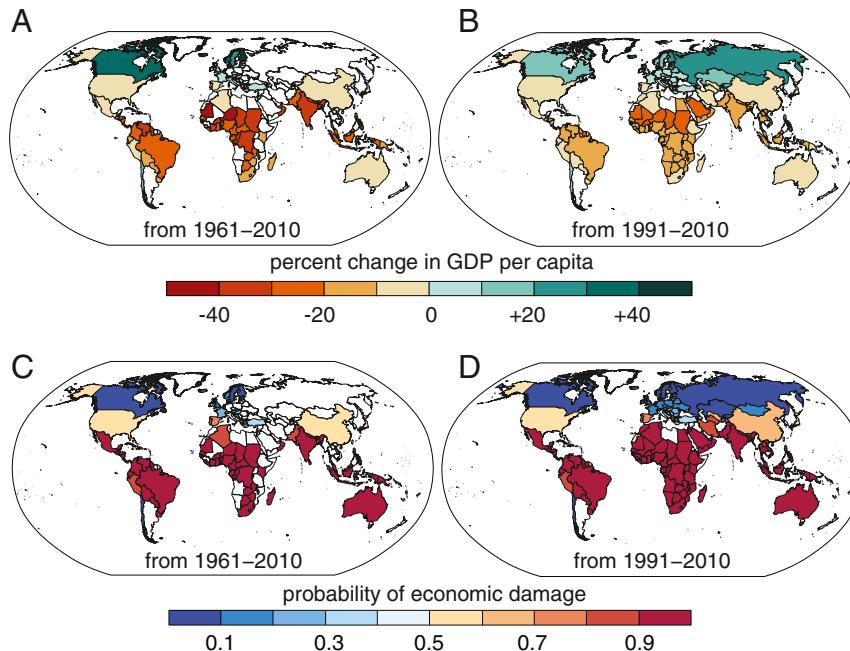
positive across all land areas (Fig. 1A), and because the differences in temperature change between countries (Fig. 1A) are small compared with the range of country-mean temperatures (Fig. 1B), the median economic response is that countries that are currently warmer than the median optimum have experienced losses, while countries that are currently colder than the median optimum have experienced benefits (Fig. 3A).

Consistent with the strong spatial correlation between temperature and GDP (23), we find a positive relationship between current GDP and impact from historical warming, with lower per capita GDP generally associated with more negative impacts (Fig. 3B). Furthermore, at a given level of wealth, warmer countries have tended to experience more negative impacts, while cooler countries have tended to experience less negative—or in some cases more positive—impacts. Because the majority of the world's warmest countries are poor (Fig. 3A and B), the majority of large negative impacts have been concentrated in poor countries (Fig. 3A and B). Likewise, because the majority of the world's richest countries are temperate or cool, the median likelihood is that the majority of rich countries have benefited.

Consistent with the strong relationship between wealth, energy consumption, and CO<sub>2</sub> emissions (24–26), we also find a positive relationship between per capita cumulative emissions and impact from historical global warming (Fig. 3C and *SI Appendix*, Fig. S1). For example, over the 1961–2010 period, all 18 of the countries whose historical cumulative emissions are less than 10 ton CO<sub>2</sub> per capita have suffered negative economic impacts, with a median impact of -27% (relative to a world without anthropogenic forcing) (Fig. 3C). Likewise, of the 36 countries whose historical emissions are between 10 and 100 ton CO<sub>2</sub> per capita, 34 (94%) have suffered negative economic impacts, with a median impact of -24%. In contrast, of the 19 countries whose historical emissions exceed 300 ton CO<sub>2</sub> per capita, 14 (74%) have benefited from global warming, with a median benefit across those 14 countries of +13%.

The net effect of these economic impacts is that country-level inequality has very likely increased as a result of global warming (Fig. 4). For example, the ratio between the top and bottom population-weighted deciles [a common measure of economic inequality (9)] has become 25% larger (5th to 95th range of -6% to +114%) during the 1961–2010 period compared with a world

## Country-level economic impact of historical global warming



**Fig. 2.** Country-level economic response to global warming. (A) The median impact on country-level per capita GDP across the >20,000 realizations of the world without anthropogenic forcing, calculated for each country over the 1961–2010 period. (B) As in A, but for the 1991–2010 period. Differences in the presence/absence of countries between the 1961–2010 and 1991–2010 periods reflect differences in the availability of country-level economic data. Differences in the magnitude of country-level values between the 1961–2010 and 1991–2010 periods reflect the influence of accumulation time on the net accumulated economic impact. (C and D) The probability that historical anthropogenic forcing has resulted in economic damage, calculated as the percentage of the >20,000 realizations that show a decrease in per capita GDP relative to the counterfactual world without anthropogenic forcing.

without global warming, with ~90% likelihood that the ratio has increased (Fig. 4C). Likewise, the ratio between the top and bottom population-weighted quintiles [another common measure (9)] has become 45% larger (5th to 95th range of +10% to +99%), with ~99% likelihood that the ratio has increased. As a result, although overall between-country inequality has decreased substantially over the past half century (Fig. 4A, refs. 9 and 10), it is “very likely” (27) that global warming has slowed that decrease (Fig. 4A and C).

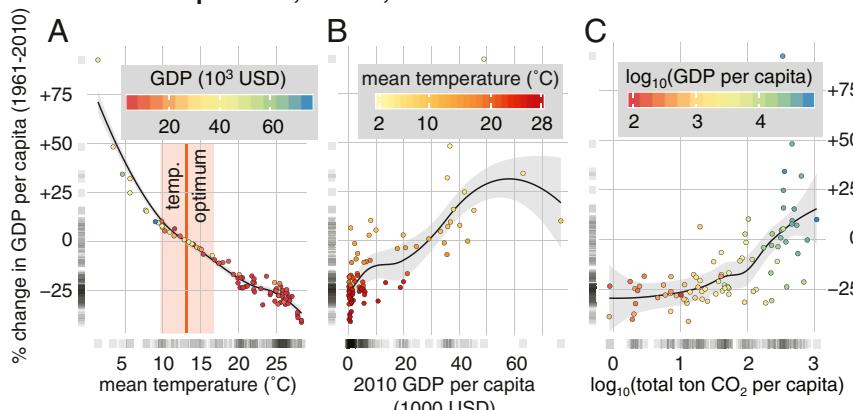
The increase in inequality between countries has resulted primarily from warming-induced penalties in poor countries, along with warming-induced benefits in some rich countries (Figs. 2A, 3B, and 4B). We find that the poorest half of the population-weighted country-level economic distribution has become relatively more poor over the 1961–2010 period, including a median impact of −17% at the poorest decile, and −30% to −31% at the next three poorest deciles (Fig. 4B). In contrast, the top half of the population-weighted country-level economic distribution has likely suffered much less—and has a much higher likelihood of having benefited—than the bottom half of the distribution (Fig. 4B).

## Discussion

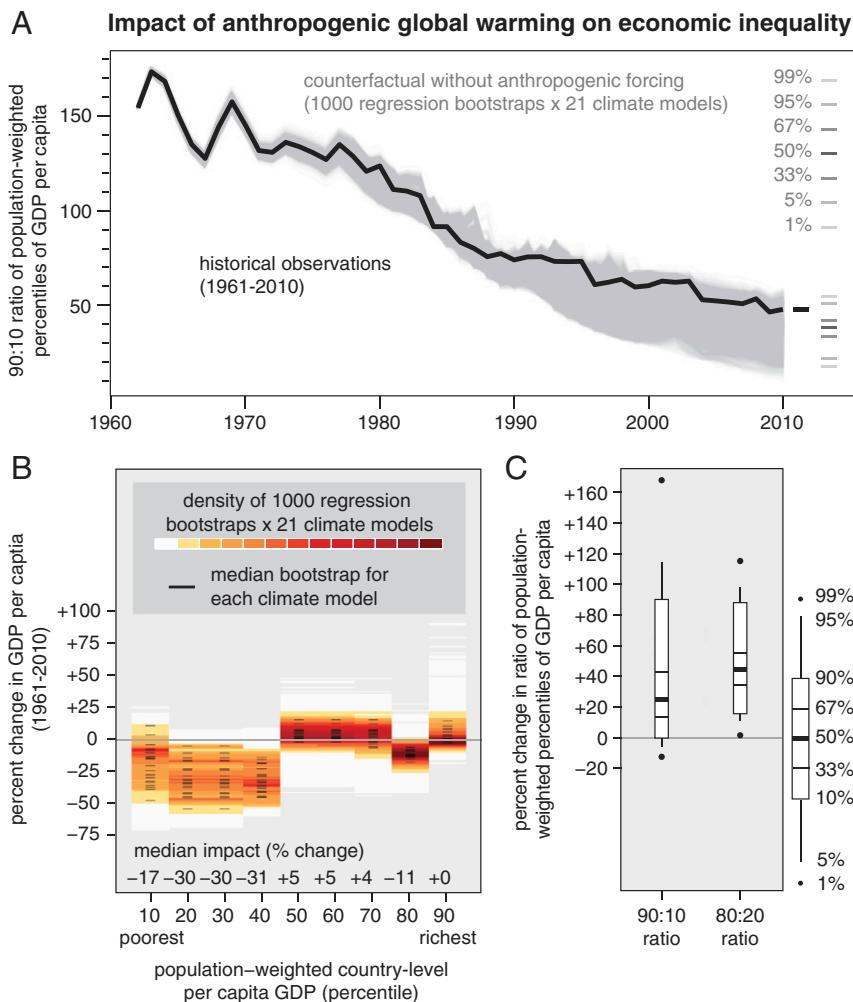
Although some canonical uncertainties in quantifying future economic impacts are largely removed when focusing on the historical period—such as future discounting uncertainty (e.g., refs. 14, 28, and 29) and the limits of accounting for future changes that fall well outside of historical experience (14)—other uncertainties must be considered.

For example, uncertainty in the exact magnitude of the temperature optimum creates uncertainty in the sign of the historical climate impact in some countries (Fig. 2C and *SI Appendix*, Table S1). However, the sign of the impact on inequality is robust (Fig. 4C), primarily because the mean temperature of so many poor countries lies in the extreme warm tail of uncertainty in the optimum (Fig. 3A and B). For these countries, it is “very likely” (27) that historical warming has reduced economic growth and lowered per capita GDP (Fig. 2C and *SI Appendix*, Table S1). As a result, although uncertainty in the magnitude of the response of regional temperature to historical forcing creates uncertainty in the magnitude of impact at a given decile of the country-level economic distribution (Fig. 4B), the sign of the impact on the lower deciles (Fig. 4B)—and therefore on inequality (Fig. 4C)—is robust.

## Relationship between the economic impact of historical global warming and temperature, wealth, and cumulative carbon emissions



**Fig. 3.** Relationship between economic impact of global warming and country-level temperature, GDP, and cumulative CO<sub>2</sub> emissions. (A) The relationship between country-level mean annual temperature and median economic impact of anthropogenic forcing over the 1961–2010 period. The orange line shows the median temperature optimum reported by Burke et al. (14), and the orange envelope shows the 5–95% range. (B) The relationship between per capita GDP in 2010 and median economic impact of historical anthropogenic forcing over the 1961–2010 period. (C) The relationship between cumulative emissions over the 1961–2010 period (calculated from ref. 32) and median economic impact of historical anthropogenic forcing over the 1961–2010 period. (A–C) Gray strip plots show the density of points along the x and y axes. The black regression line and gray envelope show the 95% confidence interval of a locally weighted regression (“loess”).



**Fig. 4.** Impact of global warming on country-level inequality over the past half century. (A) The ratio between the population-weighted 90th percentile and 10th percentile country-level per capita GDP for the historical observed time series and each of the >20,000 realizations of the world without anthropogenic forcing. (B) The density of the >20,000 realizations at each decile of the population-weighted country-level per capita GDP distribution. (C) The distribution across the >20,000 realizations of percent change in population-weighted 90:10 and 80:20 percentile ratios in the year 2010, relative to the present ratio. Calculations include only those countries that have continuous socioeconomic data from 1961 through 2010 ( $n = 86$ ).

The sign of the inequality impact is also robust to the inclusion of lagged responses (SI Appendix, Table S2). Lagged responses can compensate the growth effects of temperature fluctuations, leading to decreases in both the growth benefit in cool countries and the growth penalty in warm countries (4). These lagged responses reduce the calculated magnitude and probability of warming-induced increases in economic inequality. However, even with a 5-y lag, there is still 66% likelihood that historical warming has increased country-level inequality.

The availability of socioeconomic data also creates uncertainty. Because growth effects cumulate, the length of time over which economic impacts are evaluated can meaningfully affect results (4, 12, 14). However, data availability creates an inherent tradeoff between evaluating fewer countries over a longer period and evaluating more countries over a shorter period. We repeat our primary analysis using a larger, shorter sample. Overall, the pattern of impact is robust, but the cumulative magnitude is larger over the longer period (Figs. 2 and 3 and SI Appendix, Fig. S1). This expansion over longer periods suggests that the full impact of warming since the Industrial Revolution has been even greater than the impact calculated over the past half century.

Our approach to quantifying the impact of global warming on economic inequality is also limited by its reliance on country-level relationships between temperature and economic growth. Our analysis focuses on country-level data because their wide availability (in both space and time) allows us to use empirical relationships to quantify how historical temperature changes have affected economic outcomes around the world. The impact of climate change on the evolution of within-country inequality is

a critical question (e.g., ref. 2), but would require either strong assumptions about how within-country income distributions respond to aggregate shocks at the country level, or comprehensive subnational data on incomes (which are currently unavailable for most country-years around the world). Although our population weighting provides some indication of global-scale individual-level inequality (9), documenting the impact of global warming on within-country inequality remains an important challenge.

Many countries in our sample have experienced rapid urbanization and economic development for reasons unrelated to climate, and such trends could plausibly alter how economies respond to subsequent climate change. Because past work did not find statistically significant evidence that higher incomes reduce temperature sensitivities (4), we do not attempt to model this moderating effect here. However, if increasing urbanization or economic development has reduced the temperature sensitivity of economies over our study period, this effect will be implicitly included in our estimated impact of temperature on GDP growth and inequality—that is, we have estimated the effect of temperature on growth for economies that are rapidly urbanizing. Explicitly quantifying the role of these moderating influences is an important avenue for future work, as it will be critical for understanding how future climate change will affect the level and distribution of global income.

Trade between countries has likely already influenced the impacts of global warming on population-weighted inequality. First, a large part of the reduction in historical inequality during our sample period has been due to the unprecedented growth in incomes in East Asia [and particularly China (9, 10)], much of which was built on critical trading relationships with high-income countries. In

a no-trade counterfactual, China would likely grow much less rapidly. Thus, because of China's large population and small sensitivity to historical warming (Fig. 2), repeating our analysis in a no-trade counterfactual would likely result in smaller reductions in per capita GDP in the lower deciles of the population-weighted income distribution (Fig. 4B). However, trade can also serve as a buffer against climate shocks, particularly in poor countries (e.g., ref. 30). Thus, the economic impacts of global warming—which has substantially increased the occurrence of extremes (e.g., ref. 21)—would likely have been even greater in poor countries in a no-trade counterfactual, amplifying the impact on between-country inequality.

## Conclusions

It has been frequently observed that wealthy countries have benefited disproportionately from the activities that have caused global warming, while poor countries suffer disproportionately from the impacts (e.g., refs. 16, 17, 19, 25, and 26). Our results show that, in addition to the direct benefits of fossil fuel use, many wealthy countries have likely been made even more wealthy by the resulting global warming. Likewise, not only have poor countries not shared in the full benefits of energy consumption, but many have already been made poorer (in relative terms) by the energy consumption of wealthy countries. Given the magnitude of the warming-induced growth penalties that poor countries have already suffered, expansion of low-carbon energy sources can be expected to provide a substantial secondary development benefit (by curbing future warming-induced growth penalties), in addition to the primary benefits of increased energy access.

## Materials and Methods

**Climate Model Experiments.** We compare the Historical and Natural climate model simulations from the CMIP5 archive (20). As in Burke et al. (14), we analyze the subselection of CMIP5 realizations analyzed by the Intergovernmental Panel on Climate Change (IPCC) (31). For the Natural experiment, this includes one realization each from 21 of the participating global climate models, which are paired with the 21 corresponding Historical realizations. Note that although the socioeconomic data are available through 2010, the CMIP5 experimental protocol for the Historical and Natural experiments ends in 2005. Thus, as in Burke et al. (14), we use the IPCC's 20-y historical baseline period (1986–2005) as the baseline period for climate model bias correction.

For each country, we create 21 counterfactual historical temperature timeseries  $T_{NoAnthro}$  which remove the influence of anthropogenic forcing simulated by each of the 21 climate models. Our approach to creating the counterfactual timeseries follows the widely applied “delta method” of climate model bias correction, in which the model-simulated change in the mean is applied to the observed timeseries. For each country  $c$ , we first calculate the observed country-level population-weighted mean annual temperature timeseries  $T_{Obs}$  for the 1961–2010 time period covered by the socioeconomic data, following Burke et al. (14). Then, for each country  $c$  and climate model  $m$ , we calculate the difference in country-level population-weighted mean temperature between the Historical and Natural CMIP5 simulations, both for the 20-y period centered on the beginning of the socioeconomic data (1951–1970), and for the 20-y historical baseline period used by the IPCC (1986–2005). We then linearize the difference between the Historical and Natural simulations over the 1961–2010 period, such that the difference in 1961 is equal to the difference in the Historical and Natural means during the 20-y period centered on 1961 (1951–1970), and the difference in 2010 is equal to the difference in the Historical and Natural means during the IPCC's 20-y baseline period (1986–2005). Finally, for each year  $t$  in the 1961–2010 observed temperature timeseries, we add the linearized *Natural* minus *Historical* difference  $\Delta T$  for that year:

$$T_{NoAnthro}[t] = T_{Obs}[t] + \Delta T[t].$$

This process generates, for each country, an ensemble of 21 counterfactual timeseries  $T_{NoAnthro}$ . This 21-member ensemble reflects a combination of uncertainty in the climate response to external forcings and uncertainty arising from internal climate system variability, but removes biases in the climate model simulation of the absolute temperature magnitude and of the interannual temperature variability. [The  $T_{NoAnthro}$  timeseries corresponds to the counterfactual timeseries used in Diffenbaugh et al. (21) to calculate the contribution of the observed trend to the extreme event magnitude, except that in this case the magnitude of the counterfactual trend is calculated from the CMIP5 Natural forcing simulation.]

**Impact of Historical Temperature Change on Economic Growth.** Burke et al. (4, 14) used historical data to quantify the empirical relationship between variations in country-level temperature and country-level annual growth in per capita GDP, allowing for the marginal effect of annual temperature deviations to vary nonlinearly as a function of country-level mean temperature. As described in detail in Burke et al. (4, 14), the equation for the panel fixed-effects model is as follows:

$$\Delta \log(Y_{it}) = \beta_1 T_{it} + \beta_2 T_{it}^2 + \lambda_1 P_{it} + \lambda_2 P_{it}^2 + \mu_i + \nu_t + \theta_{1i} t + \theta_{2i} t^2 + \varepsilon_{it},$$

where  $Y_{it}$  is per capita GDP in country  $i$  in year  $t$ ,  $T$  is the average temperature in year  $t$ ,  $P$  is the average precipitation in year  $t$ ,  $\mu_i$  are country-fixed effects,  $\nu_t$  are year-fixed effects, and  $\theta_{1i}t + \theta_{2i}t^2$  are country-specific linear and quadratic time trends.

In the current study, we repeat the primary regression calculation described in Burke et al. (14), using historical data from 1961 to 2010, and bootstrapping with replacement to estimate a separate response function for each of 1,000 resamples, which we denote  $f_b$ . The uncertainty in the magnitude of the temperature optimum (Fig. 1B) creates uncertainty in exactly which countries are likely to benefit or be penalized at different levels of warming, and is the largest source of uncertainty in the response of GDP growth to elevated levels of global climate forcing (14).

We quantify the uncertainty in economic damages arising from uncertainty in the temperature optimum (e.g., Figs. 2 and 4 and *SI Appendix, Table S1*), as well as the uncertainty arising from lagged responses to temperature fluctuations (*SI Appendix, Table S2*). We also explore additional aspects of the relationship between temperature and GDP growth. For example, we find that historical temperature fluctuations explain on average 8.6% of the overall variation in country-level annual income growth fluctuations during our study period (*SI Appendix, Fig. S2*). Likewise, given the shape of the temperature–growth response function (Fig. 1B), temperature fluctuations around a stable mean will induce a negative trend in per capita GDP. However, we find that the magnitude of this effect is small compared with the impact of long-term warming (*SI Appendix, Fig. S3*).

Whereas Burke et al. (4, 14) projected economic impacts under future emissions scenarios, we calculate the accumulated economic impacts of historical temperature change. For each country  $c$  in each year  $t$ , we compare economic growth under historical observed temperatures ( $T_{Obs}$ ) with predicted growth under counterfactual temperatures ( $T_{NoAnthro}$ ). We repeat this comparison for each climate model  $m$  and each bootstrap  $j$ , yielding more than 20,000 realizations of the impact of anthropogenic forcing on economic growth in each country.

We first initialize the analysis in each country with the observed per capita GDP from the starting year  $t = 0$  of the socioeconomic data (e.g.,  $GDPcap_{Obs}[1961]$ ). Then, for each year  $t$  and using the temperature–growth response functions  $f$  estimated above, we calculate the difference in growth rate between the observed temperature and the counterfactual temperature (Fig. 1 C and D):

$$\Delta Growth[t] = f(T_{NoAnthro}[t]) - f(T_{Obs}[t]).$$

We then add that difference  $\Delta Growth[t]$  to the actual observed growth rate  $Growth_{Obs}[t]$  to calculate the counterfactual growth rate  $Growth_{NoAnthro}[t]$ :

$$Growth_{NoAnthro}[t] = Growth_{Obs}[t] + \Delta Growth[t].$$

We then multiply this counterfactual growth  $Growth_{NoAnthro}[t]$  by the accumulated counterfactual per capita GDP in the previous year ( $GDPcap_{NoAnthro}[t-1]$ ) to calculate current-year counterfactual per capita GDP:

$$GDPcap_{NoAnthro}[t] = GDPcap_{NoAnthro}[t-1] + (GDPcap_{NoAnthro}[t-1] * Growth_{NoAnthro}[t]).$$

We repeat this process through the last year of the socioeconomic data (2010), for each country in the GDP dataset.

Finally, we calculate the percent difference between the actual observed per capita GDP ( $GDPcap_{Obs}$ ) and the per capita GDP calculated for the counterfactual temperature timeseries ( $GDPcap_{NoAnthro}$ ) in the last year of the socioeconomic data (2010):

$$\Delta GDPcap = [(GDPcap_{Obs}[2010] - GDPcap_{NoAnthro}[2010]) / GDPcap_{NoAnthro}[2010]] * 100\%.$$

For each country  $c$ , we calculate  $GDPcap_{NoAnthro}$  and  $\Delta GDPcap$  for each of the 1,000 bootstrapped response functions  $f_b$ , applied to the counterfactual temperature timeseries  $T_{NoAnthro}$  from each of the 21 global climate models

(thus yielding more than 20,000 values of  $GDPcap_{NoAnthro}$  and  $\Delta GDPcap$  for each country).

Our primary analysis is focused on quantifying the impacts that historical global warming has had during the full period for which socioeconomic data are available (1961–2010). However, because the socioeconomic data do not extend to 1961 for a large number of countries, we repeat our analysis for the 1991–2010 period. For all analyses that start in 1961, we analyze only those countries that have continuous socioeconomic data from 1961 through 2010 ( $n = 86$ ); for all analyses that start in 1991, we analyze only those countries that have continuous socioeconomic data from 1991 through 2010 ( $n = 151$ ). Observed and estimated counterfactual temperatures and growth rates are the same for the years that overlap between the two periods, but growth rates are cumulated over 30 more years in the longer period, yielding larger (in absolute value) impacts on economic outcomes by the end of the period (Fig. 2).

**Quantifying the Impact of Historical Global Warming on Economic Inequality.** A number of measures of economic inequality have been developed (9). Given the limited availability of long timeseries of subnational economic data, investigations of changes in global inequality often rely on country-level metrics (e.g., refs. 9 and 10). However, when using country-level metrics, weighting by country-level population is critical to accurately capture trends in global inequality (9).

We measure global economic inequality using the ratio of the top and bottom decile ("90:10 ratio") and top and bottom quintile ("80:20 ratio") of the population-weighted country-level per capita GDP distribution. Both metrics are included among "eight of the most popular" indexes of income inequality identified by Sala-i-Martin (9). According to Sala-i-Martin (9), "The top-20-percent-to-bottom-20-percent is the ratio of the income of the person located at the top twentieth centile divided by the income of the corresponding person at the bottom twentieth centile. A similar definition applies to the top-10-percent-to-bottom-10-percent ratio." Because of the lack of availability of long timeseries of subnational economic data, we calculate these ratios using the respective percentiles of the population-weighted empirical CDF of country-level per capita GDP values (SI Appendix, Fig. S4).

We first calculate the percent difference in per capita GDP for each decile of the population-weighted country-level GDP distribution. To do so, we calculate the deciles of country-level population-weighted per capita GDP, using the countries in the 1961–2010 dataset. For each year  $t$  in the observed country-level per capita GDP dataset ( $GDPcap_{Obs}$ ), we calculate the  $p$ th percentile population-weighted GDP as the country-level per capita GDP

below which the sum of the country-level populations represents  $p$  percent of the total population of countries in the 1961–2010 dataset (SI Appendix, Fig. S4). For example, we calculate the 10th percentile population-weighted GDP as the country-level per capita GDP for which the total population of countries with lower per capita GDP is 10% of the total population of countries in the 1961–2010 dataset, and so on for each decile.

Next, we calculate the deciles of country-level population-weighted per capita GDP in each year  $t$  of each bootstrap  $j$  and climate model  $m$  of the counterfactual world without anthropogenic climate forcing ( $GDPcap_{NoAnthro}$ ). Then, for the year 2010 in each bootstrap  $j$  and climate model  $m$ , we calculate the percent difference between the observed population-weighted decile value and the counterfactual population-weighted decile value (as described for  $\Delta GDPcap$  above). For the differences in each population-weighted decile, we calculate the density distribution across all 1,000 bootstrap regressions from all 21 climate models, as well as the median value across the 1,000 bootstrap regressions for each climate model.

Finally, we quantify the between-country population-weighted economic inequality  $GDPcapHigh:Low$  as the ratio between the higher percentile (e.g., 90th) and lower percentile (e.g., 10th) population-weighted per capita GDP. We first calculate  $GDPcapHigh:Low$  in each year  $t$  of the observations ( $GDPcapHigh:Low_{Obs}$ ), and in each year  $t$  of the counterfactual world without anthropogenic climate forcing ( $GDPcapHigh:Low_{NoAnthro}$ ). Then, for each bootstrap  $j$  and climate model  $m$ , we calculate the percent difference between the observed population-weighted inequality  $GDPcapHigh:Low_{Obs}$  and the counterfactual population-weighted inequality  $GDPcapHigh:Low_{NoAnthro}$  in the year 2010:

$$\Delta GDPcapHigh:Low = \frac{[(GDPcapHigh:Low_{Obs}[2010] - GDPcapHigh:Low_{NoAnthro}[2010]) / GDPcapHigh:Low_{NoAnthro}[2010]]}{100\%}.$$

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