

Global non-linear effect of temperature on economic production

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Growing evidence demonstrates that climatic conditions can have a profound impact on the functioning of modern human societies^{1,2}, but effects on economic activity appear inconsistent. Fundamental productive elements of modern economies, such as workers and crops, exhibit highly non-linear responses to local temperature even in wealthy countries^{3,4}. In contrast, aggregate macroeconomic productivity of entire wealthy countries is reported not to respond to temperature⁵, while poor countries respond only linearly^{5,6}. Resolving this conflict between micro and macro observations is critical to understanding the role of wealth in coupled human–natural systems^{7,8} and to anticipating the global impact of climate change^{9,10}. Here we unify these seemingly contradictory results by accounting for non-linearity at the macro scale. We show that **overall economic productivity is non-linear in temperature for all countries, with productivity peaking at an annual average temperature of 13 °C and declining strongly at higher temperatures**. The relationship is globally generalizable, unchanged since 1960, and apparent for agricultural and non-agricultural activity in both rich and poor countries. These results provide the first evidence that economic activity in all regions is coupled to the global climate and establish **a new empirical foundation for modelling economic loss in response to climate change**^{11,12}, with important implications. If future adaptation mimics past adaptation, unmitigated warming is expected to reshape the global economy by **reducing average global incomes** roughly 23% by 2100 and **widening global income inequality**, relative to scenarios without climate change. In contrast to prior estimates, expected global losses are approximately linear in global mean temperature, with median losses many times larger than leading models indicate.

Economic productivity—the efficiency with which societies transform labour, capital, energy, and other natural resources into new goods or services—is a key outcome in any society because it has a direct impact on individual wellbeing. While it is well known that temperature affects the dynamics of virtually all chemical, biological and ecological processes, how temperature effects recombine and aggregate within complex human societies to affect overall economic productivity remains poorly understood. Characterizing this influence remains a fundamental problem both in the emerging field of coupled human–natural systems and in economics more broadly, as it has implications for our understanding of historical patterns of human development and for how the future economy might respond to a changing climate.

Prior analyses have identified how specific components of economic production, such as crop yields, respond to temperature using high-frequency micro-level data^{3,4}. Meanwhile, macro-level analyses have documented strong correlations between total economic output and temperature over time^{5,6} and across space^{13,14}, but it is unknown whether these results are connected, and if so, how. In particular, strong responses of output to temperature observed in micro data from wealthy countries are not apparent in existing macro studies⁵. If

wealthy populations actually are unaffected by temperature, this could indicate that **wealth and human-made capital are substitutes for natural capital** (for example, the composition of the atmosphere) in economic activity^{5,7}. Resolving this apparent discrepancy thus has central implications for understanding the nature of sustainable development⁷.

Numerous basic productive components of an economy display a highly non-linear relationship with daily or hourly temperature¹. For example, labour supply⁴, labour productivity⁶, and crop yields³ all decline abruptly beyond temperature thresholds located between 20 °C and 30 °C (Fig. 1a–c). However, it is unclear how these abrupt

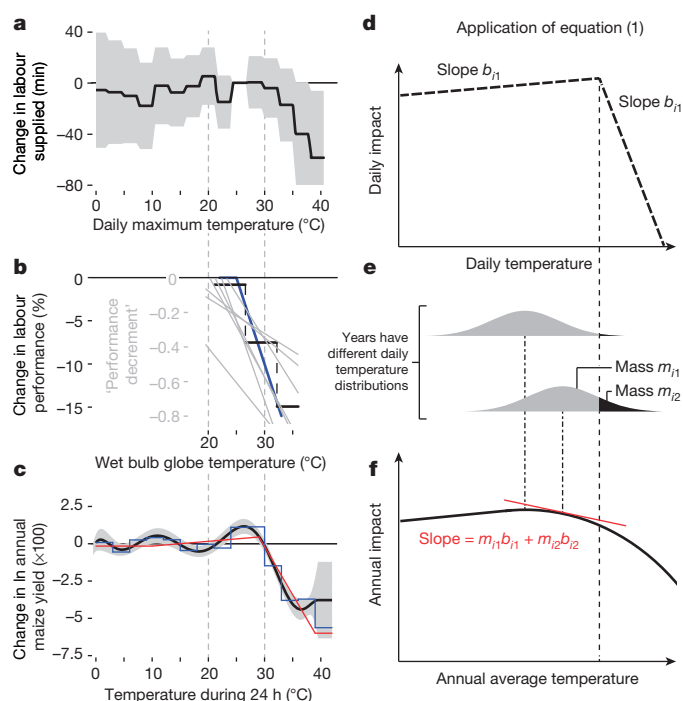


Figure 1 | Highly non-linear micro responses generate smooth and shifted macro response. **a–c**, Highly non-linear micro-level responses of labour supply⁴ (**a**), labour performance⁶ (**b**) and crop yield³ (**c**) to daily temperature exposure exhibit similar ‘kinked’ structures between 20 and 30 °C. **d**, **e**, These micro-level responses ($f_i(T)$ in equation (1); **d**) map onto country-level distributions of temperatures across different locations and times within that country ($g_i(T - \bar{T})$ in equation (1); **e**). Shifts in country-level distributions correspond to changes in average annual temperature, altering the fraction of unit-hours (m_{i1} and m_{i2}) exposed to different regions of the micro-level response in **d**, **f**. Aggregating daily impacts according to equation (1) maps annual average temperature to annual output as a non-linear and concave function that is smoother than the micro response with a lower optimum ($Y(\bar{T})$ in equation (1)).

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declines at the micro level are reflected in coarser macro-level data. When production is integrated over large regions (for example, countries) or long units of time (for example, years), there is a broad distribution of momentary temperatures to which individual components of the economy (for example, crops or workers) are exposed. If only the hottest locations or moments cause abrupt declines in output, then when combined with many cooler and highly productive moments they would sum to an aggregate level of output that only declines modestly when aggregate average temperature increases.

To fix ideas, let function $f_i(T)$ describe the productive contribution of an individual productive unit in industry i (for example, a firm) relative to instantaneous (for example, daily) temperature T (Fig. 1d). For a given country, period, and industry, denote the fraction of unit-hours spent below the critical temperature threshold as m_{i1} and the fraction above as m_{i2} (Fig. 1e). The full distribution of unit-hours across all temperatures is $g_i(T - \bar{T})$, centred at average temperature $\bar{T}$. Assume $g_i(\cdot)$ is mean zero. If productivity loss within a single productive unit-hour has limited impact on other units, as suggested by earlier findings^{8,15}, then aggregate production Y is the sum of output across industries, each integrated over all productive unit-hours in the country and period:

$$Y(\bar{T}) = \sum_i Y_i(\bar{T}) = \sum_i \int_{-\infty}^{\infty} f_i(T) \cdot g_i(T - \bar{T}) dT \quad (1)$$

As $\bar{T}$ rises and a country warms on average, m_{i2} increases gradually for all productive units (Fig. 1e). This growing number of hours beyond the temperature threshold imposes gradual but increasing losses on total output $Y(\bar{T})$.

Equation (1) predicts that $Y(\bar{T})$ is a smooth concave function (Fig. 1f) with a derivative that is the average derivative of $f_i(T)$ weighted by the number of unit-hours in each industry at each daily temperature. It also predicts that $Y(\bar{T})$ peaks at a temperature lower than the threshold value in $f_i(T)$, if the slope of $f_i(T)$ above the threshold is steeper than minus the slope below the threshold, as suggested by micro-scale evidence. These predictions differ fundamentally from notions that macro responses should closely mirror highly non-linear micro responses^{6,16}. Importantly, while aggregate productivity losses ought to occur contemporaneous with temperature changes, these changes might also influence the long-run trajectory of an economy's output^{5,15}. This could occur, for example, if temporary contemporaneous losses alter the rate of investment in new productive units, thereby altering future production. See Supplementary Equations 1–14 for details.

We test these predictions using data on economic production¹⁷ for 166 countries over the period 1960–2010. In an ideal experiment, we would compare two identical countries, warm the temperature of one and compare its economic output to the other. In practice, we can approximate this experiment by comparing a country to itself in years when it is exposed to warmer- versus cooler-than-average temperatures¹⁸ due to naturally occurring stochastic atmospheric changes. Heuristically, an economy observed during a cool year is the ‘control’ for that same society observed during a warmer ‘treatment’ year. We do not compare output across different countries because such comparisons are probably confounded, distinguishing our approach from cross-sectional studies that attribute differences across countries to their temperatures¹³.

We estimate how economic production changes relative to the previous year—that is, **annual economic growth**—to purge the data of secular factors in each economy that evolve gradually⁵. We deconvolve economic growth to account for: (1) all constant differences between countries, for example, culture or history; (2) all common contemporaneous shocks, for example, global price changes or technological innovations; (3) country-specific quadratic trends in growth rates, which may arise, for example, from changing political institutions or economic policies; and (4) the possibly non-linear effects of annual average temperature and rainfall. This approach is more reliable than only adjusting for observed variables because it accounts for unobserved time-invariant and time-trending covariates, allows these covariates to influence different countries in different ways, and outperforms alternative models along numerous dimensions¹⁵ (see Supplementary Information). In essence, we analyse whether country-specific deviations from growth trends are non-linearly related to country-specific deviations from temperature and precipitation trends, after accounting for any shocks common to all countries.

We find country-level economic production is smooth, non-linear, and concave in temperature (Fig. 2a), with a maximum at 13 °C, well below the threshold values recovered in micro-level analyses and consistent with predictions from equation (1). Cold-country productivity increases as annual temperature increases, until the optimum. Productivity declines gradually with further warming, and this decline accelerates at higher temperatures (Extended Data Fig. 1a–g). This

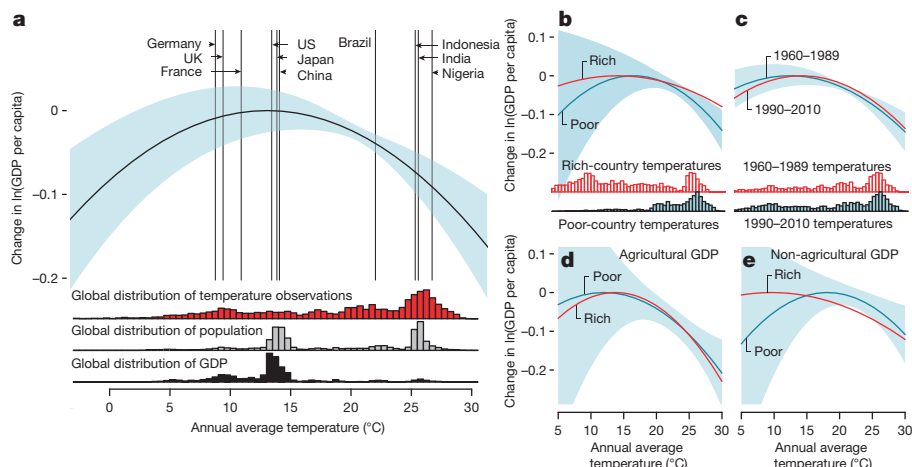


Figure 2 | Effect of annual average temperature on economic production. **a**, Global non-linear relationship between annual average temperature and change in log gross domestic product (GDP) per capita (thick black line, relative to optimum) during 1960–2010 with 90% confidence interval (blue, clustered by country, $N = 6,584$). Model includes country fixed effects, flexible trends, and precipitation controls (see Supplementary Methods). Vertical lines indicate average temperature for selected countries, although averages

are not used in estimation. Histograms show global distribution of temperature exposure (red), population (grey), and income (black). **b**, Comparing rich (above median, red) and poor (below median, blue) countries. Blue shaded region is 90% confidence interval for poor countries. Histograms show distribution of country-year observations. **c**, Same as **b** but for early (1960–1989) and late (1990–2010) subsamples (all countries). **d**, Same as **b** but for agricultural income. **e**, Same as **b** but for non-agricultural income.

result is globally representative and not driven by outliers (Extended Data Fig. 1h). It is robust to estimation procedures that allow the response of countries to change as they become richer (Extended Data Fig. 1i and Supplementary Table 1), use higher-order polynomials or restricted cubic splines to model temperature effects (Extended Data Fig. 1j–k), exclude countries with few observations, exclude major oil producers, exclude China and the United States, account for continent-specific annual economic shocks¹⁹, weaken assumptions about trends in growth, account for multiple lags of growth, and use alternative economic data sources²⁰ (Extended Data Table 1).

Accounting for delayed effects of temperature, which might be important if countries ‘catch up’ after temporary losses, increases statistical uncertainty but does not alter the net negative average effect of hot temperatures (Extended Data Fig. 2a–c). **This ‘no catch up’ behaviour is consistent with the observed response to other climatological disturbances, such as tropical cyclones¹⁵.**

While much of global economic production is clustered near the estimated temperature optimum (Fig. 2a, black histogram), both rich and poor countries exhibit similar non-linear responses to temperature (Fig. 2b). Poor tropical countries exhibit larger responses mainly because they are hotter on average, not because they are poorer (Extended Data Fig. 1i and Supplementary Table 1). There is suggestive evidence that rich countries might be somewhat less affected by temperature, as previously hypothesized⁵, but their response is statistically indistinguishable from poor countries at all temperatures (Extended Data Fig. 2d–f and Extended Data Table 2). Although the estimated total effect of high temperatures on rich countries is substantially less certain because there are few hot, rich countries in the sample, **the non-linearity of the rich-country response alone is statistically significant ($P < 0.1$;** Extended Data Table 2), and we estimate an 80% likelihood that the marginal effect of warming is negative at high temperatures in these countries (Extended Data Fig. 2m). Our finding that rich countries respond non-linearly to temperature is consistent with recent county-level results in the United States⁸.

Our non-linear results are also consistent with the prior finding of no linear correlation between temperature and growth in rich countries⁵. Because the distribution of rich-country temperatures is roughly symmetrical about the optimum, linear regression recovers no association. Accounting for non-linearity reconciles this earlier result (Extended Data Fig. 3a and Supplementary Table 3) but reverses how wealth and technology are understood to mediate economic responses to temperature.

We do not find that technological advances or the accumulation of wealth and experience since 1960 has fundamentally altered the relationship between productivity and temperature. Results using data from 1960–1989 and 1990–2010 are nearly identical (Fig. 2c). In agreement with recent micro-level evidence^{8,21}, substantial observed warming over the period apparently did not induce notable adaptation.

Consistent with micro-level findings that both agricultural and non-agricultural labour-related productivity are highly non-linear in instantaneous temperature^{3,4,6}, we find agricultural and non-agricultural aggregate production are non-linear in average annual temperature for both rich and poor countries (Fig. 2d, e and Extended Data Fig. 2g–l). Low temperature has no significant effect on these subsamples, although limited poor-country exposure to these temperatures severely limits statistical precision. High temperatures have significant negative effects in all cases for poor countries, and significant or marginally significant effects for rich countries (Extended Data Fig. 2p–u).

A global non-linear response of economic production to annual temperature has important implications for the likely economic impact of climate change. We find only weak suggestive evidence that richer populations are less vulnerable to warming, and no evidence that experience with high temperatures or technological advances since 1960 have altered the global response to temperature. This suggests that adaptation to climatic change may be more difficult than

previously believed^{9,10}, and that the accumulation of wealth, technology and experience might not substantially mitigate global economic losses during this century^{8,21}.

We quantify the potential impact of warming on national and global incomes by combining our estimated non-linear response function with ‘business as usual’ scenarios (Representative Concentration Pathway (RCP)8.5) of future warming and different assumptions regarding future baseline economic and population growth²² (see Supplementary Information). This approach assumes future economies respond to temperature changes similarly to today’s economies—perhaps a reasonable assumption given the observed lack of adaptation during our 50-year sample.

In 2100, we estimate that unmitigated climate change will make 77% of countries poorer in per capita terms than they would be without climate change. Climate change may make some countries poorer in the future than they are today, depending on what secular growth rates are assumed. With high baseline growth and unmitigated climate change (RCP8.5 and Shared Socio-economic Pathway (SSP)5; see Supplementary Information), we project that **5% of countries are poorer in 2100 than today** (Fig. 3a), **while with low growth, 43% are** (SSP3; Fig. 3b).

Differences in the projected impact of warming are mainly a function of countries’ baseline temperatures, since warming raises productivity in cool countries (Fig. 4). In particular, Europe could benefit from increased average temperatures. Because warming harms productivity in countries with high average temperatures, incomes in poor regions are projected to fall relative to a world without climate change with high confidence ($P < 0.01$), regardless of the statistical approach used. Models allowing for delayed effects project more negative impacts in colder wealthy regions; projections assuming rich and poor countries respond differently (Fig. 2b) are more uncertain because fewer data are used to estimate each response (Extended Data Fig. 4).

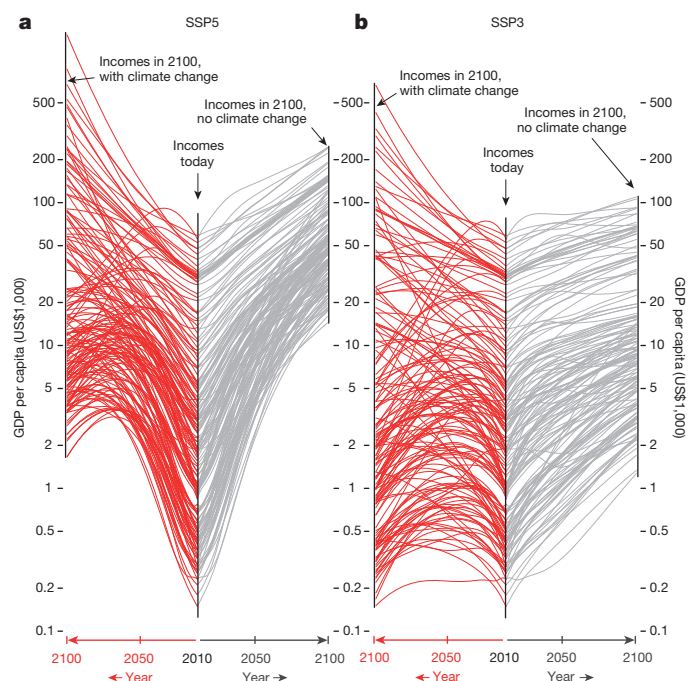


Figure 3 | Country-level income projections with and without temperature effects of climate change. **a, b,** Projections to 2100 for two socioeconomic scenarios²² consistent with RCP8.5 ‘business as usual’ climate change: **a,** SSP5 assumes high baseline growth and fast income convergence; **b,** SSP3 assumes low baseline growth and slow convergence. Centre in each panel is 2010, each line is a projection of national income. Right (grey) are incomes under baseline SSP assumptions, left (red) are incomes accounting for non-linear effects of projected warming.

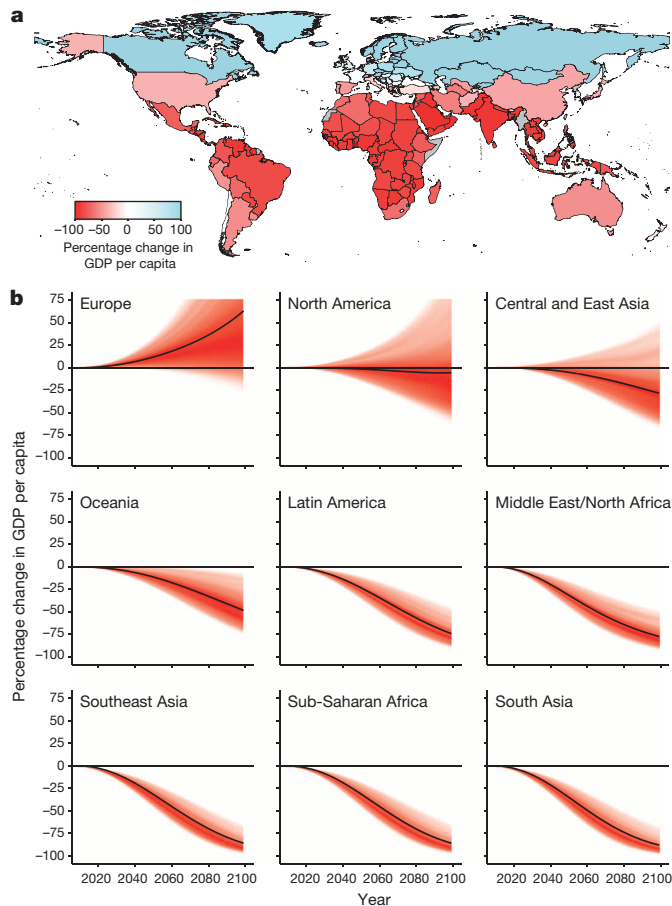


Figure 4 | Projected effect of temperature changes on regional economies. **a**, **b**, Change in GDP per capita (RCP8.5, SSP5) relative to projection using constant 1980–2010 average temperatures. **a**, Country-level estimates in 2100. **b**, Effects over time for nine regions. Black lines are projections using point estimates. Red shaded area is 95% confidence interval, colour saturation indicates estimated likelihood an income trajectory passes through a value²⁷. Base maps by ESRI.

The impact of warming on global economic production is a population-weighted average of country-level impacts in Fig. 4a. Using our benchmark model (Fig. 2a), climate change reduces projected global output by 23% in 2100 (best estimate, SSP5) relative to a world without climate change, although statistical uncertainty allows for positive impacts with probability 0.29 (Fig. 5a and Extended Data Table 3). Estimates vary in magnitude, but not in structure, depending on the statistical approach (Fig. 5b and Extended Data Table 3). Models with delayed impacts project larger losses because cold countries gain less, while differentiated rich–poor models have smaller losses (statistical uncertainty allows positive outcomes with probability 0.09–0.40). Models allowing both delayed impacts and differentiated rich–poor responses (the most flexible approach) project global losses 2.2 times larger than our benchmark approach. In all cases, the likelihood of large global losses is substantial: global losses exceed 20% of income with probability 0.44–0.87 (Extended Data Table 3 and Extended Data Fig. 5).

Accounting for the global non-linear effect of temperature is crucial to constructing income projections under climate change because countries are expected to become both warmer and richer in the future. In a previous analysis in which a linear relationship was assumed and no significant linear effect was observed in rich countries⁵, it was hypothesized that countries adapted effectively to temperature as they became wealthier. Under this hypothesis, the impacts of future warming should lessen over time as countries become richer. In contrast,

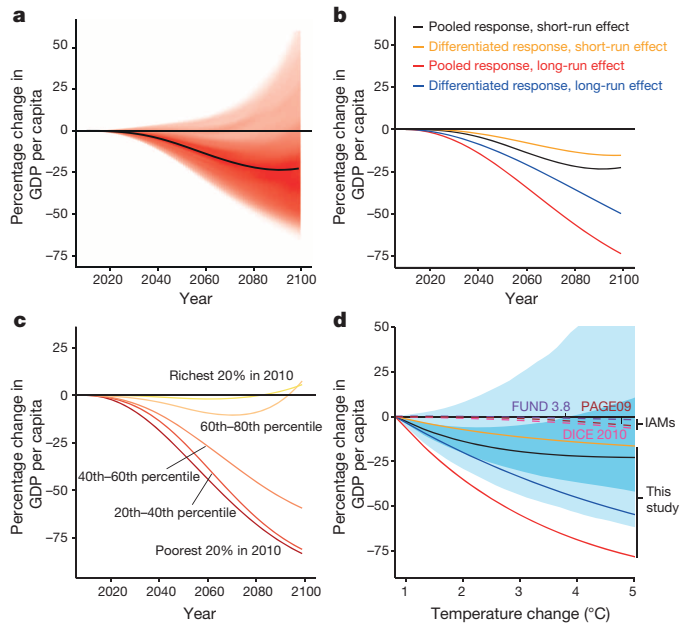


Figure 5 | Global damage estimates arising from non-linear effects of temperature. **a**, Change in global GDP by 2100 using benchmark model (Fig. 2a). Calculation and display are the same as Fig. 4. **b**, Same as **a** (point estimate only) comparing approaches to estimating temperature effects (pooled/differentiated: rich and poor countries assumed to respond identically/differently, respectively; short run/long run: effects account for 1 or 5 years of temperature, respectively; see Supplementary Methods). **c**, Mean impacts by 2100 income quintile (benchmark model). **d**, Projected income loss in 2100 (SSP5) for different levels of global mean temperature increase, relative to pre-industrial temperatures. Solid lines marked as in **b**. Blue shaded areas are interquartile range and 5th–95th percentile estimates. Dashed lines show corresponding damages from major integrated assessment models (IAMs)¹².

when we account for the non-linear effect of temperature historically, we find that **rich and poor countries behave similarly at similar temperatures, offering little evidence of adaptation**. This indicates that we cannot assume rich countries will be unaffected by future warming, nor can we assume that the impacts of future warming will attenuate over time as countries become wealthier. Rather, the impact of additional warming worsens over time as countries become warmer. As a result, projections using linear and non-linear approaches diverge substantially—by roughly 50–200% in 2100 (Extended Data Fig. 3c, d)—highlighting the importance of accounting for this non-linearity when assessing the impacts of future warming.

Strong negative correlation between baseline income and baseline temperature indicates that **warming may amplify global inequality because hot, poor countries will probably suffer the largest reduction in growth** (Fig. 5c). In our benchmark estimate, average income in the poorest 40% of countries declines 75% by 2100 relative to a world without climate change, while the richest 20% experience slight gains, since they are generally cooler. Models with delayed impacts do not project as dramatic differences because colder countries also suffer large losses (Extended Data Fig. 5).

We use our results to construct an empirical ‘damage function’ that maps global temperature change to global economic loss by aggregating country-level projections. Damage functions are widely used in economic models of global warming, but previously relied on theory for structure and rough estimates for calibration^{11,12}. Using our empirical results, we project changes to global output in 2100 for different temperature changes (Fig. 5d; see Supplementary Information) and compare these to previously estimated damage functions¹². Commonly used functions are within our estimated uncertainty, but differ in two important respects.

First, our projected global losses are roughly linear—and slightly concave—in temperature, not quadratic or exponential as previously theorized. Approximate linearity results from the broad distribution of temperature exposure within and across countries, which causes the country-weighted average derivative of the productivity function in Fig. 2a to change little as countries warm and prevents abrupt transitions in global output even though the contribution of individual productive units are highly non-linear (see Fig. 1). Global losses are slightly concave in global temperature because the effect of compounding negative growth declines mechanically over time (Extended Data Fig. 6e and Supplementary Information). These properties are independent of the growth scenario and response function (Extended Data Fig. 6a).

Second, the slope of the damage function is large even for slight warming, generating **expected costs of climate change 2.5–100 times larger than prior estimates for 2 °C warming, and at least 2.5 times larger for higher temperatures** (Extended Data Fig. 6b–d). Notably, our estimates are based only on temperature effects (or effects for which historical temperature has been a proxy), and so do not include other potential sources of economic loss associated with climate change, such as tropical cyclones¹⁵ or sea-level rise²³, included in previous damage estimates.

If societies continue to function as they have in the recent past, climate change is expected to reshape the global economy by substantially reducing global economic output and possibly amplifying existing global economic inequalities, relative to a world without climate change. **Adaptations such as unprecedented innovation²⁴ or defensive investments²⁵ might reduce these effects, but social conflict² or disrupted trade²⁶—either from political restrictions or correlated losses around the world—could exacerbate them.**

Online Content Methods, along with any additional Extended Data display items and Source Data, are available in the online version of the paper; references unique to these sections appear only in the online paper.

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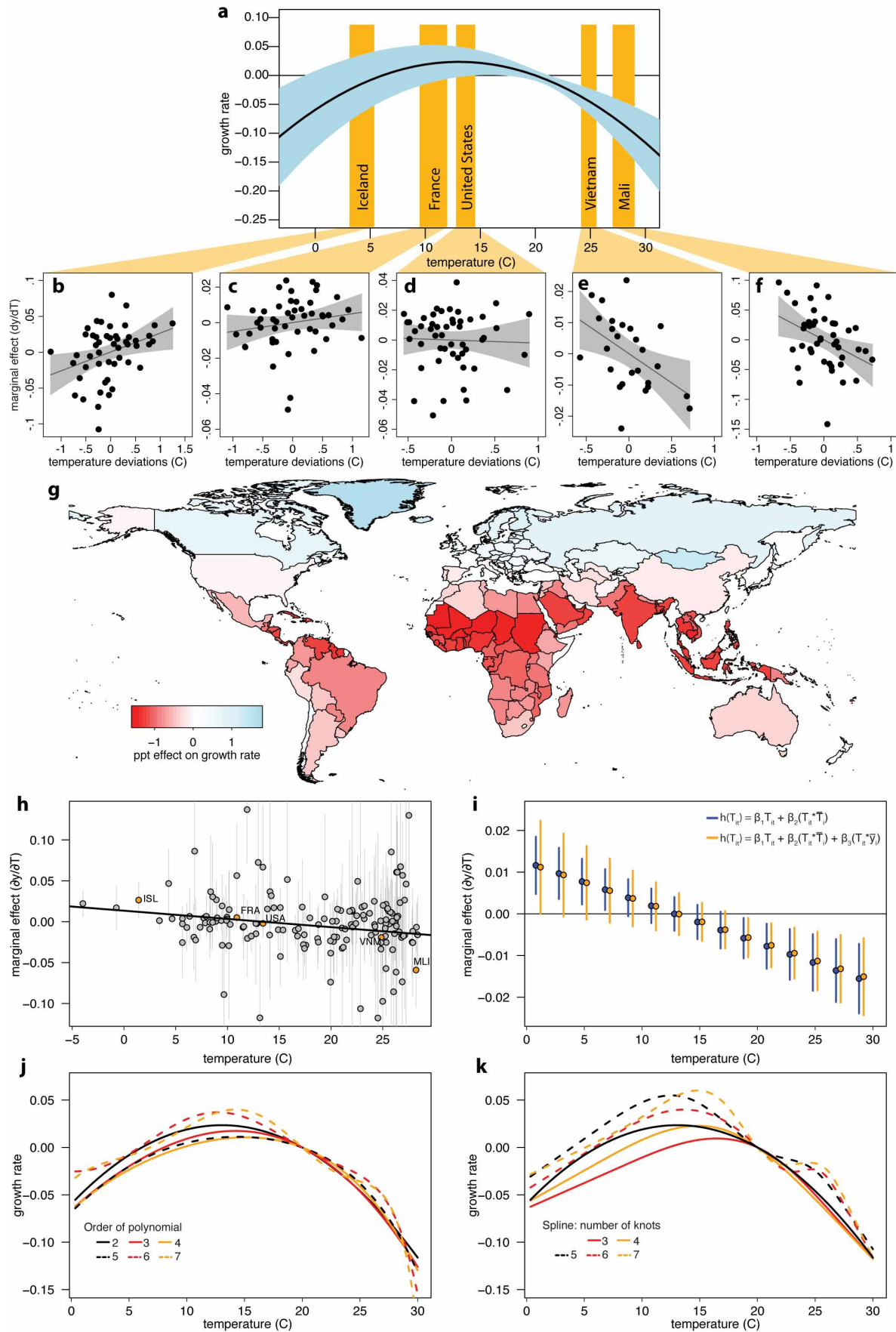
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Supplementary Information is available in the online version of the paper.

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Author Information Replication data have been deposited at the Stanford Digital Repository (<http://purl.stanford.edu/wb587wt4560>). Reprints and permissions information is available at www.nature.com/reprints. The authors declare no competing financial interests. Readers are welcome to comment on the online version of the paper. Correspondence and requests for materials should be addressed to M.B. (mburke@stanford.edu).

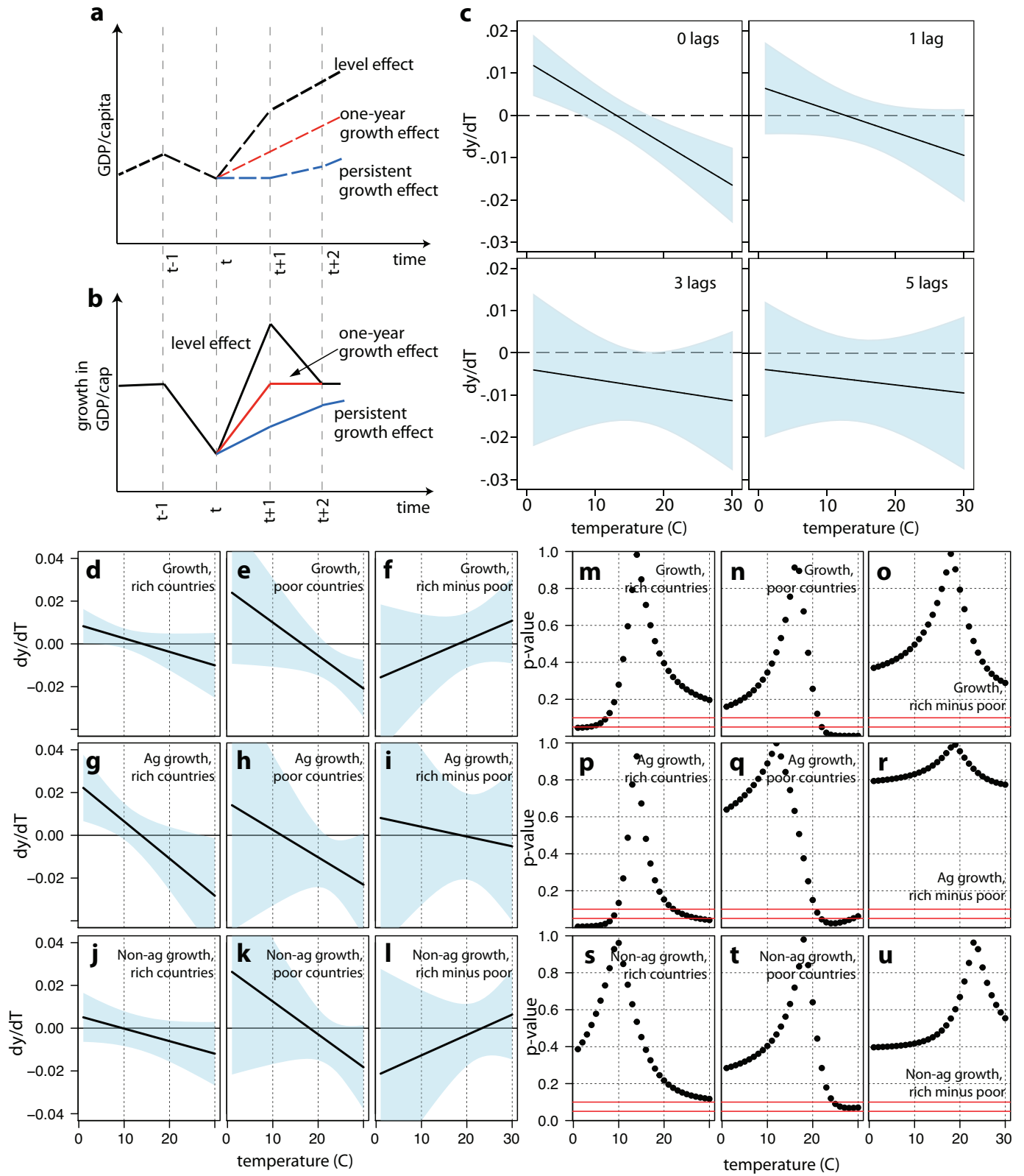


Extended Data Figure 1 | Understanding the non-linear response function.

a, Response function from Fig. 2a. **b–f**, The global non-linear response reflects changing marginal effects of temperature at different mean temperatures. Plots represent selected country-specific relationships between temperature and growth over the sample period, after accounting for the controls in Supplementary Equation (15); dots are annual observations for each country, dark line the estimated linear relationship, grey area the 95% confidence interval. **g**, Percentage point effect of uniform 1°C warming on country-level growth rates, as estimated using the global relationship shown in **a**. A value of -1 indicates that a country growing at $3\% \text{ yr}^{-1}$ during the baseline period is projected to grow at $2\% \text{ yr}^{-1}$ with $+1^\circ\text{C}$ warming. ppt, percentage point. **h**, Dots represent estimated marginal effects for each country from separate linear time-series regressions (analogous to slopes of lines in **b–f**), and grey lines the 95% confidence interval on each. The dark black line plots the derivative $\frac{\partial Y}{\partial T}$ of the estimated global response function in Fig. 2a. **i**, Global

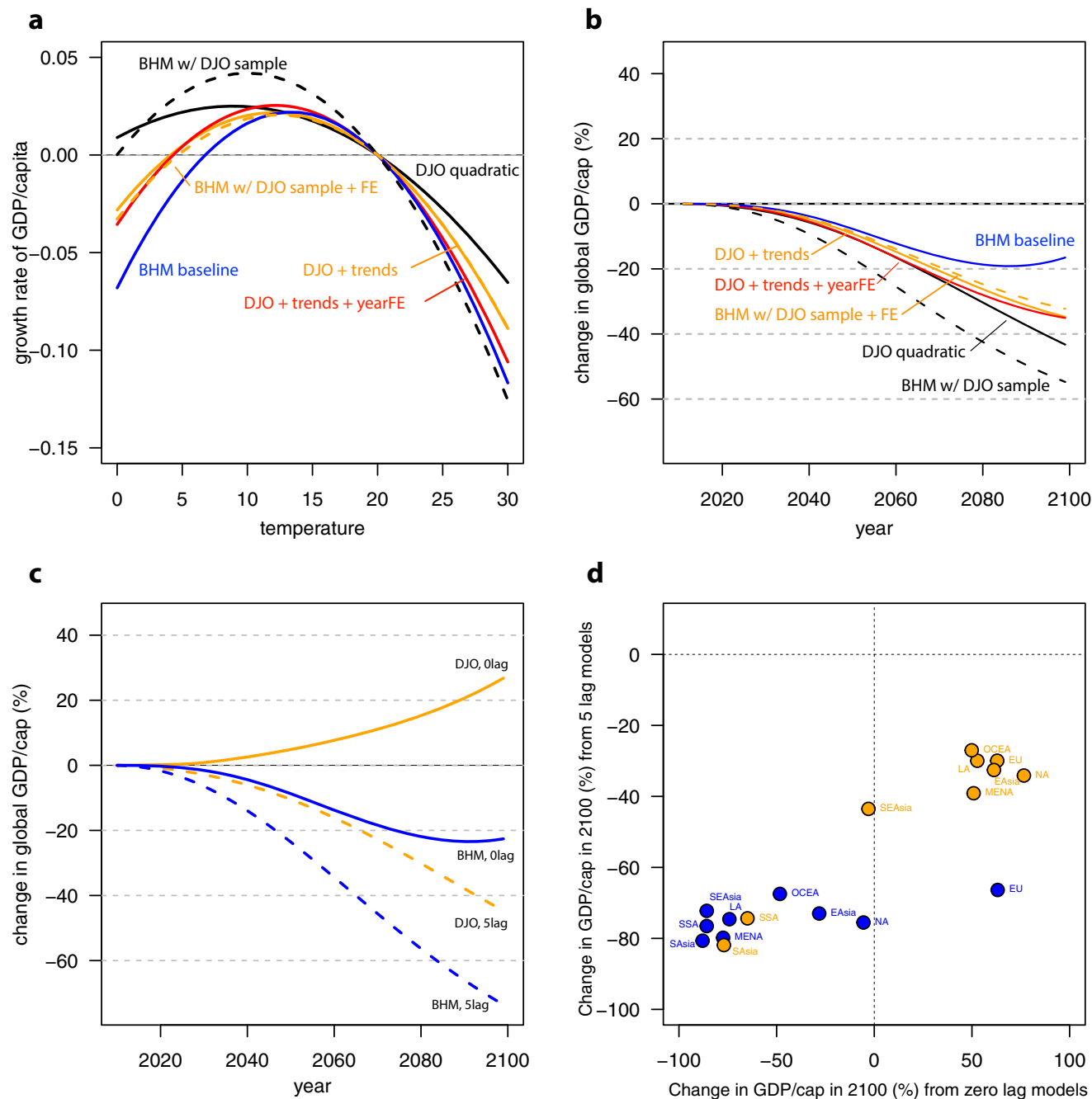
non-linearity is driven by differences in average temperature, not income. Blue dots (point estimates) and lines (95% confidence interval) show marginal effects of temperature on growth evaluated at different average temperatures, as estimated from a model that interacts country annual temperature with country average temperature (see Supplementary Equation (17); $\frac{\partial Y}{\partial T_{it}} = \hat{\beta}_1 + \hat{\beta}_2 \cdot \bar{T}_i$).

Orange dots and lines show equivalent estimates from a model that includes an interaction between annual temperature and average GDP. Point estimates are similar across the two models, indicating that the non-linear response is not simply due to hot countries being poorer on average. **j–k**, More flexible functional forms yield similar non-linear global response functions. **j**, Higher-order polynomials in temperature, up to order 7. **k**, Restricted cubic splines with up to 7 knots. Solid black line in both plots is quadratic polynomial shown in **a**. Base maps by ESRI.



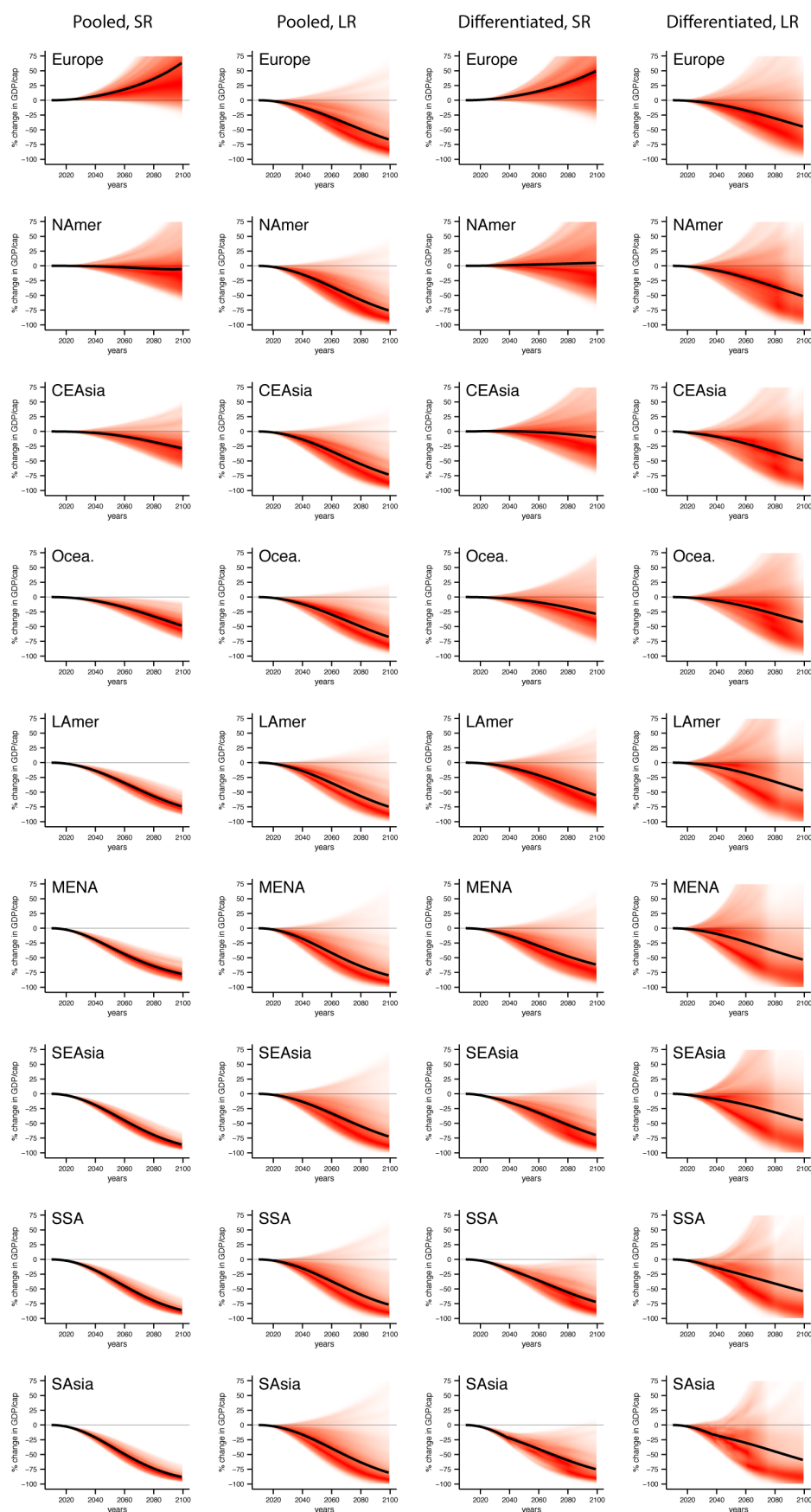
Extended Data Figure 2 | Growth versus level effects, and comparison of rich and poor responses. **a**, Evolution of GDP per capita given a temperature shock in year t . Black line shows a level effect, with GDP per capita returning to its original trajectory immediately after the shock. Red line shows a 1-year growth effect, and blue line a multi-year growth effect. **b**, Corresponding pattern in the growth in per-capita GDP. Level effects imply a slower-than-average growth rate in year t but higher-than-average rate in $t + 1$. Growth effects imply lower rates in year t and then average rates thereafter (for a 1-year shock) or lower rates thereafter (if a 1-year shock has persistent effects on growth). **c**, Cumulative marginal effect of temperature on growth as additional lags are included; solid line indicates the sum of the contemporaneous and lagged marginal effects at a given temperature level, and the blue areas its 95% confidence interval. **d–l**, Testing the null that slopes of rich- and poor-country response functions are zero, or the same as one another, for quadratic

response functions shown in Fig. 2. Black lines show the point estimate for the marginal effect of temperature on rich-country production for different initial temperatures (blue shading is 95% confidence interval) (**d**, **g**, **j**), the marginal effect poor-country production for different initial temperatures (**e**, **h**, **k**), and the estimated difference between the marginal effect on rich- and poor-country production compared at each initial temperature (**f**, **i**, **l**). **d–f**, Effects on economy-wide per-capita growth (corresponding to Fig. 2b). **g–i**, Agricultural growth. **j–l**, Non-agricultural growth. **m–u**, Corresponding P values. Each point represents the P value on the test of the null hypothesis that the slope of the rich-country response is zero at a given temperature (**m**, **p**, **s**), that the slope of the poor-country response is zero (**n**, **q**, **t**), or that rich- and poor-country responses are equal (**o**, **r**, **u**) for overall growth, agricultural growth, or non-agricultural growth, respectively. **m–u**, Red lines at the bottom of each plot indicate $P = 0.10$ and $P = 0.05$.



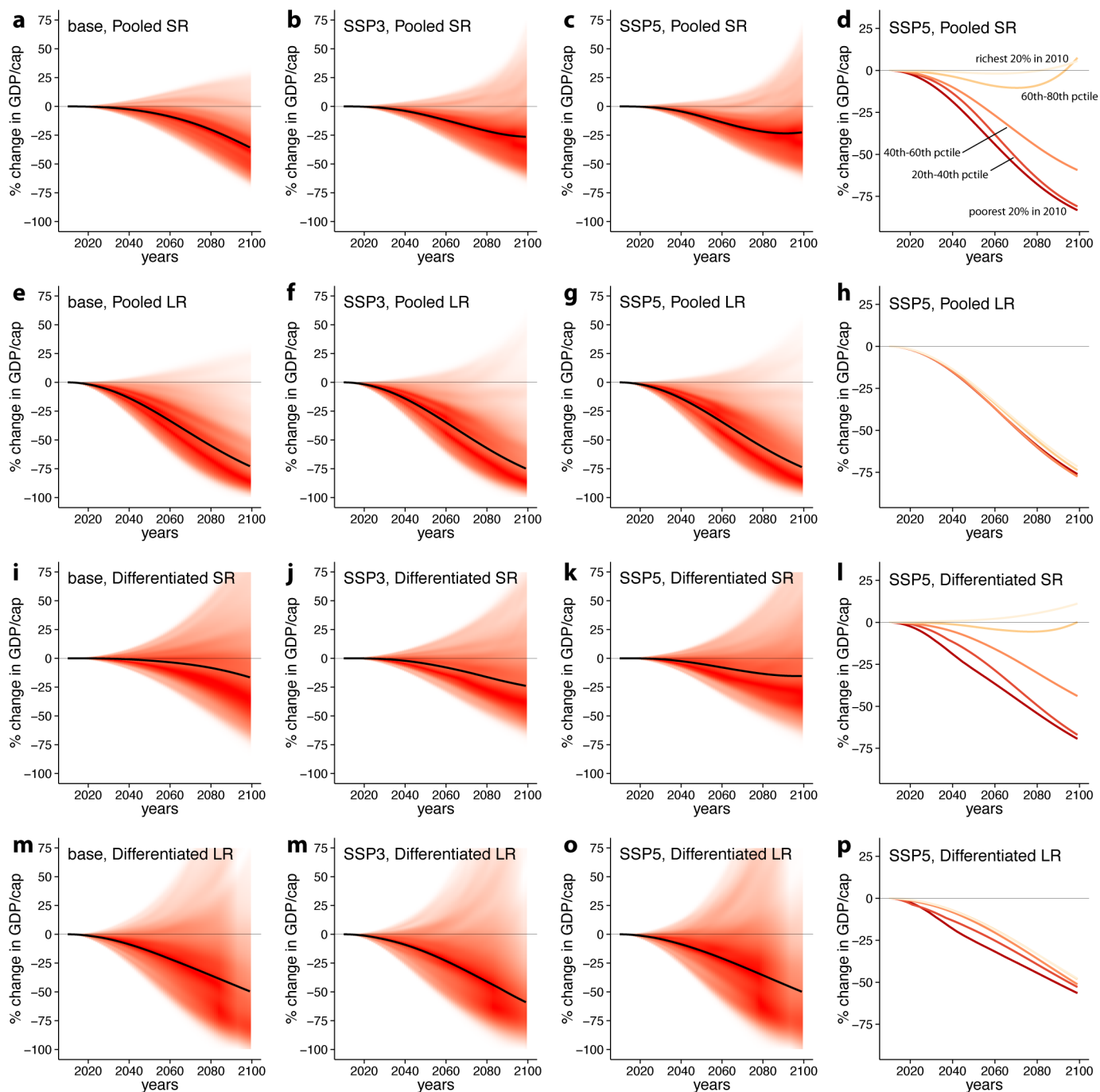
Extended Data Figure 3 | Comparison of our results and those of Dell, Jones and Olken⁵. **a**, Allowing for non-linearity in the original Dell, Jones and Olken (DJO)⁵ data/analysis indicates a similar temperature–growth relationship as in our results (BHM) under various choices about data sample and model specification (coefficients in Supplementary Table 3). **b**, Projections of future global impacts on per-capita GDP (RCP8.5, SSP5) using the re-estimated non-linear DJO response functions in **a** again provide similar estimates to our baseline BHM projection (shown in blue, and here using the sample of countries with > 20 years of data to match the DJO preferred sample).

c, Projected global impacts differ substantially between DJO and BHM if DJO's original linear results are used to project impacts. Lines show projected change in global GDP per capita by 0- and 5-lag pooled non-linear models in BHM (blue), and 0- and 5-lag linear models in DJO (orange). **d**, Projected regional impacts also differ strongly between BHM's non-linear and DJO's linear approach. Plot shows projected impacts on GDP per capita in 2100 by region, for the 0-lag model (x-axis) and 5-lag model (y-axis), with BHM estimates in blue and DJO estimates in orange. See Supplementary Discussion for additional detail.



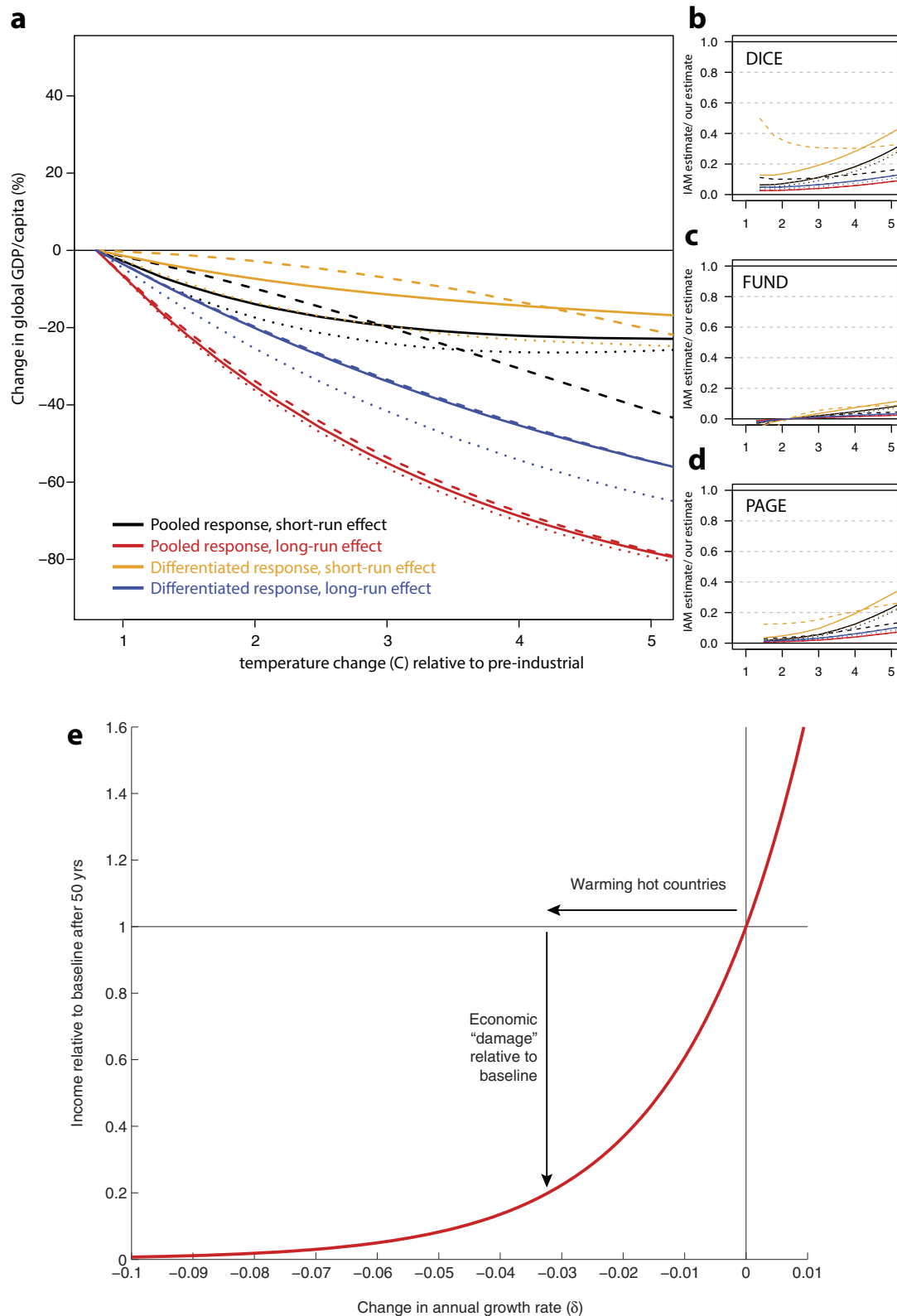
Extended Data Figure 4 | Projected impact of climate change (RCP8.5, SSP5) on regional per capita GDP by 2100, relative to a world without climate change, under the four alternative historical response functions. Pooled short-run (SR) response (column 1), pooled long-run (LR) response

(column 2), differentiated SR response (column 3), differentiated LR response (column 4). Shading is as in Fig. 5a. CEAsia, Central and East Asia; LAmer, Latin America; MENA, Middle East/North Africa; NAmer, North America; Ocea, Oceania; SAsia, South Asia; SEAsia, South-east Asia; SSA, sub-Saharan Africa.



Extended Data Figure 5 | Projected impact of climate change (RCP8.5) by 2100 relative to a world without climate change, for different historical response functions and different future socioeconomic scenarios. a–p. The first three columns show impacts on global per-capita GDP (analogous to Fig. 5a), for the three different underlying socioeconomic scenarios and four different response functions shown in Fig. 5b. Last column (d, h, l, p) shows

impact on per capita GDP by baseline income quintile (as in Fig. 5c), for SSP5 and the different response functions. Colours correspond to the income quintiles as labelled in d. Globally aggregated impact projections are more sensitive to choice of response function than projected socioeconomic scenario, with response functions that allow for accumulating effects of temperature (LR) showing more negative global impacts but less inequality in these impacts.



Extended Data Figure 6 | Estimated damages at different levels of temperature increase by socioeconomic scenario and assumed response function, and comparison of these results to damage functions in IAMs.

a, Percentage loss of global GDP in 2100 under different levels of global temperature increase, relative to a world in which temperatures remained at pre-industrial levels (as in Fig. 5d). Colours indicated in figure represent different historical response functions (as in Fig. 5b). Line type indicates the underlying assumed socioeconomic scenario: dash indicates ‘base’ (United Nations medium variant population projections, future growth rates are

country-average rates observed 1980–2010), dots indicate SSP3, solid lines indicate SSP5. **b–d**, The ratio of estimated damages from each IAM using data from ref. 12 (shown in Fig. 5d) to damages in **a**. Colours as in **a** for results from this study; IAM results are fixed across scenarios and response functions. Temperature increase is in °C by 2100, relative to pre-industrial levels. **e**, Explanation for why economic damage function is concave: increasingly negative growth effects have diminishing cumulative impact in absolute levels over finite periods (see Supplementary Discussion). Red curve is $e^{\delta\zeta}$ after $\zeta = 50$ years.

Extended Data Table 1 | Regression estimates for global sample, main estimate and robustness

	(1) Base	(2) >20yrs	(3) No oil	(4) No US/China	(5) ContYr FE	(6) ContYr + noTrend	(7) No YrFE	(8) LinearTime	(9) LDV 1lag	(10) LDV 3lags	(11) PWT
Temp.	0.0127*** (0.0038)	0.0135*** (0.0038)	0.0128*** (0.0036)	0.0128*** (0.0038)	0.0142*** (0.0037)	0.0133*** (0.0034)	0.0103*** (0.0039)	0.0128*** (0.0043)	0.0087** (0.0039)	0.0062* (0.0038)	0.0072* (0.0039)
Temp. sq.	-0.0005*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)	-0.0004*** (0.0001)	-0.0004*** (0.0001)	-0.0005*** (0.0001)	-0.0004*** (0.0001)	-0.0003*** (0.0001)	-0.0004*** (0.0001)
Precip.	0.0145 (0.0100)	0.0148 (0.0100)	0.0130 (0.0101)	0.0148 (0.0101)	0.0124 (0.0106)	0.0084 (0.0098)	0.0159 (0.0107)	0.0137 (0.0100)	0.0165* (0.0095)	0.0201** (0.0098)	0.0195* (0.0109)
Precip. sq.	-0.0047* (0.0026)	-0.0049* (0.0026)	-0.0040 (0.0025)	-0.0048* (0.0026)	-0.0041 (0.0027)	-0.0021 (0.0023)	-0.0045* (0.0026)	-0.0035 (0.0023)	-0.0047* (0.0024)	-0.0052** (0.0024)	-0.0038 (0.0028)
Constant	1.4575** (0.6444)	0.0740 (0.0633)	1.4522** (0.6228)	1.4707** (0.6507)	-0.0362 (0.0411)	-0.0819** (0.0370)	-0.8024** (0.3366)	-0.7693*** (0.0517)	-11.3227*** (0.7957)	-28.3451*** (2.0763)	0.0643 (0.0467)
Observations	6584	6477	6090	6484	6584	6584	6584	6584	6418	6086	6627
R squared	0.286	0.278	0.275	0.284	0.367	0.267	0.240	0.219	0.286	0.289	0.220
Optimum	13.06	13.39	12.64	13.09	14.92	17.40	12.74	13.40	11.92	9.98	9.88

Unless otherwise indicated, all models include country fixed effects, year fixed effects, and quadratic country time trends, with errors clustered at the country level. Temperature is measured in °C and precipitation in metres. Columns: (1) main specification, (2) as in column 1 but excluding countries with fewer than 20 years of growth data, (3) as in column 1 but dropping large oil exporting countries, (4) as in column 1 but dropping United States and China, (5) as in column 1 but adding continent-by-year fixed effects, (6) as in column 1 but adding continent-by-year fixed effects and dropping country time trends, (7) as in column 1 but dropping year fixed effects, (8) as in column 1 but only linear time trend, (9–10) as in column 1 but adding 1 or 3 lags of per capita growth (that is, lagging the dependent variable), (11) as in column 1 but using growth data from Penn World Tables. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Extended Data Table 2 | Comparing temperature effects on per-capita growth in rich versus poor countries

	(1) Base	(2) poor-yr FE	(3) >20Yrs	(4) >20Yrs+poor-yr FE	(5) ContYr FE	(6) ContYr + noTrend
Temperature (β_1)	0.0089** (0.0044)	0.0069 (0.0050)	0.0085* (0.0044)	0.0063 (0.0050)	0.0099* (0.0054)	0.0146*** (0.0052)
Temperature sq. (β_2)	-0.0003* (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0003 (0.0002)	-0.0005*** (0.0002)
Temperature * 1[poor] (β_3)	0.0165 (0.0182)	0.0193 (0.0187)	0.0246 (0.0186)	0.0275 (0.0191)	0.0115 (0.0147)	0.0016 (0.0147)
Temperature sq. * 1[poor] (β_4)	-0.0005 (0.0004)	-0.0005 (0.0004)	-0.0006 (0.0004)	-0.0007 (0.0004)	-0.0004 (0.0004)	0.0001 (0.0003)
Observations	6452	6452	6345	6345	6452	6452
R squared	0.291	0.299	0.284	0.293	0.372	0.270
$\beta_1 + \beta_3$	0.0254	0.0262	0.0332	0.0338	0.0215	0.0162
se($\beta_1 + \beta_3$)	0.0177	0.0180	0.0181	0.0184	0.0130	0.0123
$\beta_2 + \beta_4$	-0.0008	-0.0008	-0.0009	-0.0009	-0.0007	-0.0004
se($\beta_2 + \beta_4$)	0.0004	0.0004	0.0004	0.0004	0.0003	0.0003
Rich-country optimum (C)	14.1	12.2	14.2	12.2	19.2	15.1
Poor-country optimum (C)	16.5	17.2	17.8	18.3	16.2	20.6

Unless otherwise indicated, all models include a quadratic in precipitation, country fixed effects, year fixed effects, and quadratic country time trends, with errors clustered at the country level. Temperature is measured in °C. Columns: (1) main specification with the climate variables interacted with an indicator for whether a country is poor, (2) as in column 1 but allowing the year fixed effects to differ across rich and poor countries, (3) as in column 1 but restricting sample to countries with at least 20 observations, (4) as in column 1 but restricting sample to countries with at least 20 observations and allowing year fixed effects to differ across rich and poor countries, (5) as in column 1 but adding continent-by-year fixed effects, (6) as in column 1 but adding continent-by-year fixed effects and dropping country time trends (as in ref. 5). The estimated linear and quadratic effects in poor countries (and their standard errors) are given in the bottom rows of the table, along with the estimated temperature optima for rich and for poor countries. Asterisks indicate statistical significance at the 1% (***), 5% (**), and 10% (*) levels for coefficients in the main part of the table.

Extended Data Table 3 | Projected impacts of climate change on global GDP per capita by 2100 under RCP8.5, relative to a world without climate change

Historical model	Statistic	Projected impacts under alternate scenarios of future population/income growth <i>% impact relative to world without climate change</i>		
		base	SSP3	SSP5
Pooled model	point est.	-36	-26	-23
	5th	-65	-60	-58
	25th	-50	-42	-39
	50th	-35	-24	-21
	75th	-16	2	5
	95th	27	67	66
	% runs < 0	85	73	71
	% runs < -10	79	66	63
	% runs < -20	71	56	51
Pooled with 5 lags	point est.	-73	-75	-74
	5th	-94	-94	-94
	25th	-85	-85	-84
	50th	-70	-68	-67
	75th	-48	-41	-41
	95th	28	55	51
	% runs < 0	91	89	89
	% runs < -10	89	86	87
	% runs < -20	87	84	84
Rich/poor model	point est.	-16	-24	-15
	5th	-67	-62	-61
	25th	-43	-42	-37
	50th	-17	-19	-12
	75th	22	16	27
	95th	103	82	101
	% runs < 0	63	66	60
	% runs < -10	55	59	51
	% runs < -20	48	50	44
Rich/poor with 5 lags	point est.	-50	-59	-50
	5th	-93	-90	-92
	25th	-75	-69	-72
	50th	-40	-39	-30
	75th	20	45	65
	95th	265	379	428
	% runs < 0	69	66	62
	% runs < -10	65	63	59
	% runs < -20	61	59	56

Estimates are from four different response functions (as in Fig. 5b) estimating how growth responds to temperature, and three different scenarios of how future populations and incomes will evolve without climate change. The left column indicates the historical response function on which the projections are based, the second column describes the statistic being reported (either the point estimate, a given percentile in the bootstrapped distribution of projections, or the percentage of total runs projecting impacts more negative than zero, -10%, or -20%), and the last three columns give percentage impacts for three different future scenarios: 'base' (United Nations medium variant population projections, future growth rates without climate change equal to country-average rates observed 1980–2010), SSP3, and SSP5.