A top-down approach to projecting market impacts of climate change

Sections A and B extend the Methods by providing the specific steps and coefficients used in calculating medium-run and short-run impacts, respectively. Section C provides supporting information, additional results, and robustness checks. Section D reports results for values of inequality aversion greater than reported in the main text. The file lemoine_kapnick DAMAGES_CODE.ZIP contains Matlab code and data. It also reports the optimal carbon taxes (social costs of carbon) implied by integrating the medium-run damage estimates into the DICE integrated assessment model.

A Step-by-Step Guide and Coefficients for Medium-Run Impacts

[1] estimates medium-run damages from climate change by comparing average climatic and economic outcomes over 1970–1985 to average outcomes over 1986–2000. The results describe, for instance, whether countries that happened to warm faster than average over this period grew more or less slowly than countries that happened to warm more slowly. [1] uses a “poor country” dummy variable to allow climate impacts to vary by countries’ per-capita GDP. For our purposes of projecting future impacts, a continuous measure of the effect of per-capita GDP on climate impacts is more useful than a binary variable. We therefore reestimate their relationship (on their original data) using an interaction between log per-capita GDP and temperature, an interaction between log per-capita GDP and precipitation, and a non-interacted log per-capita GDP main effect. Redoing the second specification in their Table 7, which includes region fixed effects and robust standard errors, we obtain the following vector of coefficients $\beta^M$:

$$\beta^M = \begin{bmatrix} -0.372 \\ 2.25 \\ -0.0586 \\ -0.0645 \end{bmatrix},$$

with the coefficients ordered as the temperature term, the temperature-GDP interaction term, the precipitation term, and the precipitation-GDP interaction term. The temperature variable is an annual population-weighted average in degrees Celsius, and the precipitation variable measures a year’s precipitation in units of 100mm, constructed as a population-weighted average of a year’s total precipitation at each gridpoint. Consistent with [1], warming reduces growth at average initial per-capita GDP and reduces growth more strongly in poorer countries. The temperature-GDP interaction is significant at the 1% level, and the GDP main effect (not reported) is negative and significant at the 5% level. The corresponding covariance matrix $\Omega^M$ is:

$$\Omega^M = \begin{bmatrix} 0.450 & -0.0325 & -0.00642 & -0.0193 \\ -0.0325 & 0.652 & -0.00910 & -0.00325 \\ -0.00642 & -0.00910 & 0.00889 & 0.00174 \\ -0.0193 & -0.00325 & 0.00174 & 0.0298 \end{bmatrix}.$$

Note that the square root of the $n$th element on the diagonal of $\Omega^M$ is the standard error of the $n$th element of $\beta^M$. We treat the sampling distribution of the estimator as a normal distribution.
Table: Model Mean Grid Cell Resolution (Degrees)

<table>
<thead>
<tr>
<th>Institute</th>
<th>Model ID</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 BCC</td>
<td>bcc-csm1-1</td>
<td>2.8</td>
</tr>
<tr>
<td>2 NCAR</td>
<td>CCSM4</td>
<td>1.1</td>
</tr>
<tr>
<td>3 NSF/DOE NCAR</td>
<td>CESM1-CAM5</td>
<td>1.1</td>
</tr>
<tr>
<td>4 FIO</td>
<td>FIO-ESM</td>
<td>2.2</td>
</tr>
<tr>
<td>5 NOAA/GFDL</td>
<td>GFDL CM3</td>
<td>2.2</td>
</tr>
<tr>
<td>6 NOAA/GFDL</td>
<td>GFDL ESM2G</td>
<td>2.2</td>
</tr>
<tr>
<td>7 NASA/GISS</td>
<td>GISS-E2-H</td>
<td>2.2</td>
</tr>
<tr>
<td>8 NASA/GISS</td>
<td>GISS-E2-R</td>
<td>2.2</td>
</tr>
<tr>
<td>9 NIMR</td>
<td>HadGEM2-AO</td>
<td>1.5</td>
</tr>
<tr>
<td>10 IPSL</td>
<td>IPSL-CM5A-LR</td>
<td>2.7</td>
</tr>
<tr>
<td>11 IPSL</td>
<td>IPSL-CM5A-MR</td>
<td>1.8</td>
</tr>
<tr>
<td>12 AORI</td>
<td>MIROCS3.2</td>
<td>1.4</td>
</tr>
<tr>
<td>13 JAMSTEC</td>
<td>MIROC-ESM</td>
<td>2.8</td>
</tr>
<tr>
<td>14 JAMSTEC</td>
<td>MIROC-ESM-CHEM</td>
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</tr>
<tr>
<td>15 MRI</td>
<td>MRI-CGCM3</td>
<td>1.1</td>
</tr>
<tr>
<td>16 NCC</td>
<td>NorESM1-M</td>
<td>2.2</td>
</tr>
<tr>
<td>17 NCC</td>
<td>NorESM1-ME</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Figure S1: The seventeen CMIP5 models used in the medium-run analysis.

Therefore, any sample vector $\omega^M$ for the historical relationship has probability density $p(\omega^M)$ given by the multivariate normal density function with mean $\beta^M$ and variance $\Omega^M$.

Using the law of conditional probability, we write the desired density using $p(\omega^M)$:

\[ p(\psi^M) = \int p(\psi^M | \omega^M) p(\omega^M) d\omega^M. \]

It remains to find the conditional density $p(\psi^M | \omega^M)$. To estimate this relationship for a given $\omega^M$, we construct a panel dataset of the seventeen CMIP5 models listed in Figure S1, with each model simulated along each of the four Representative Concentration Pathways. We use all of the CMIP5 simulations that were available for download from the Earth System Grid LLNL data node with all four RCPs. The data files are from 2011–2013. Here and in the short-run analysis, the population data is constructed from 2.5 arc-minute gridded data from [2]. For each model simulation, we convert its temperature and precipitation data into the population-weighted average annual temperature for each country in each decade, the population-weighted average annual precipitation for each country in each decade, and the global mean surface temperature in each decade. We use the CMIP5 data for 2015–2095, yielding eight decadal timesteps beginning with 2015–2024. First-differencing the data leaves us with seven timesteps. The robustness checks below explore alternative timesteps covering 5 and 15 years.

The next step is to convert the panel of temperature changes $\Delta T_{kmt}$ and precipitation changes $\Delta P_{kmt}$ for each country $k$ in each decade $t$ of each climate model-RCP combination $m$ into a panel of country-level impacts $I^M_{kmt}$. We do this by applying the coefficients in a sampled $\omega^M$ to the simulated changes in temperature and precipitation and to forecasts of per-capita GDP $y_{kt}$ (described below):

\[ I^M_{kmt} = \left[ \omega^M_T + \omega^M_T \ln (y_{kt}/7.897) \right] \Delta T_{kmt} + \left[ \omega^M_P + \omega^M_P \ln (y_{kt}/7.897) \right] \Delta P_{kmt}, \]
where the subscripts on $\omega^M$ indicate elements of the vector by identifying the coefficient they correspond to in the adapted regression from [1] and where 7.897 is the mean of initial (i.e., 1970) log GDP per capita in the medium-run data from [1]. The vector $I^M_{km}$ gives the change in the growth rate (in percentage points) for country $k$ in each decade $t$ of climate model-RCP combination $m$ as a result of the projected change in climatic variables. Positive values indicate benefits of climate change; negative values indicate damages. We project impacts under the assumption that the historical relationship holds in the future and that impacts are approximately linear in country-level temperature and precipitation (as seems to have been the case in past years [1]). Upon obtaining this panel of impacts, we aggregate them to the desired regional scale (which could be global, country-level, or anything in between) using methods described below. This aggregation results in an impacts vector $I^M_{rm}$ for each region $r$. We also aggregate country-level GDP per capita $y_{kt}$ to regional GDP per capita $y_{rt}$ using the population projections described below.

Finally, regressing the panel of impacts for region $r$ (containing $17 \times 4 \times 7$ observations) on the change in global mean surface temperature in the corresponding model-time pairs, on $\ln(y_{rt}/y_{r0})$, on the interaction between the global temperature variable and $\ln(y_{rt}/y_{r0})$, and on a constant yields coefficients on the temperature term and on the temperature-GDP interaction term. These coefficients and their covariance matrix define a sampling distribution, and we calculate $p(\psi^M_r|\omega^M)$ from the multivariate normal distribution with mean and variance defined by this sampling distribution. Importantly, this regression is used only to calculate conditional covariances between variables of interest and simulated impacts conditional on $\omega^M$. The vector $\omega^M$ itself derives from a regression that is concerned with identification in an economic sense.

To forecast country-level GDP per capita $y_{kt}$, we require forecasts of GDP and population for each country in each timestep. As described in the Methods, initial GDP per capita comes from the World Bank’s purchasing power parity-adjusted, constant-dollars dataset for the year 2010. Year 2010 population also comes from a World Bank dataset. To aid intuition, the calculations for the maps in the main text (i.e., where each country is its own region) hold GDP and population fixed, in which case we use the year 2010 values at all timesteps. In order to project population and GDP in other calculations, we use the recently developed Shared Socioeconomic Pathways. In particular, we use the June 12, 2013 “illustrative” OECD version of each of the five SSPs. These versions were the most recent at the time of analysis. The main results all use SSP2, which is the scenario of “middle” challenges. At each timestep, we calculate the growth rates implied by the chosen socioeconomic scenario and apply them to the GDP per capita and population calculated for the previous timestep, where we begin with the year 2010 World Bank values. Once we calculate time $t$ impacts for a given $\omega^M$, we adjust the growth of GDP per capita for these estimates, which means that we calculate impacts sequentially and use climate-adjusted GDP per capita in the later impact calculations. For nearly all countries and scenarios, climate-adjusted GDP increases over time because SSP2 assumes positive growth in per-capita GDP and because only limited warming occurs over any given decade. In particular, the poorest countries see their per-capita GDP increase over the century in all cases examined. We do not adjust per-capita GDP for climate impacts in the short-run estimation described below because those impacts refer to variability rather than to average growth rates.

When aggregating country-level growth rate impacts to the regional level, we allow for preferences that prefer smooth consumption profiles over space. Conventional integrated assessment
models (and, indeed, much economics literature) use the following functional form to aggregate consumption over time or over possible states of the world:

\[ U(c) = \sum_{s=1}^{N} u(c_s), \]

where \( u(c_s) = \frac{c_s^{1-\eta}}{1-\eta} \) for \( \eta \neq 1 \) and \( u(c_s) = \ln(c_s) \) for \( \eta = 1 \),

where \( s \) indicates the state or the time period, depending on the setting, and bold script indicates a vector. This form is known as isoelastic or power utility. The parameter \( \eta \) is the (constant) coefficient of relative risk aversion, with larger values indicating greater degrees of risk aversion. When aggregating consumption over time, the parameter \( \eta \) is the inverse of the intertemporal elasticity of substitution. Larger values of \( \eta \) indicate a greater desire to smooth consumption over time: larger values of \( \eta \) make us prefer present consumption to future consumption when we expect the future to be wealthier. In the present case, we use this functional form to aggregate consumption over countries within a region, with larger values indicating a greater desire to smooth consumption over space (i.e., greater inequality aversion). This approach is equivalent to using a utilitarian social welfare function to aggregate individuals’ utility when each individual’s utility is the same isoelastic function of his or her own consumption.

In order to calculate the growth rate impacts for region \( r \) in time \( t \), we first convert the time \( t \) GDP per capita vectors for the countries in region \( r \) into equivalent time \( t \) consumption \( y_{rt} \) by the representative agent in region \( r \):

\[
y_{rt} = \left[ (1 - \eta) \frac{\sum_{k \in R} L_{kt} y_{kt}^{1-\eta}}{\sum_{k \in R} L_{kt}} \right] \frac{1}{1-\eta} \text{ for } \eta \neq 1, \quad \text{and } y_{rt} = \exp \left[ \frac{\sum_{k \in R} L_{kt} \ln(y_{kt})}{\sum_{k \in R} L_{kt}} \right] \text{ for } \eta = 1,
\]

where \( y_{kt} \) and \( L_{kt} \) are GDP per capita and population in country \( k \) at time \( t \) and \( R \) is the set of countries in region \( r \). Similar conversions apply to the vector of time \( t + 1 \) GDP per capita in the presence of time \( t \) climate impacts and to the vector of time \( t + 1 \) GDP per capita in the absence of time \( t \) climate impacts. The climate impacts for region \( r \) at time \( t \) are then given by the difference between the growth of the representative agent’s equivalent consumption in the presence of time \( t \) climate impacts and in the absence of climate impacts:

\[
I_{rmt} = 100 \ast \left( \left( \frac{y_{rm(t+1)}}{y_{rt}} \right)^{0.1} - \left( \frac{\hat{y}_{r(t+1)}}{y_{rt}} \right)^{0.1} \right),
\]

where we express impacts in terms of the annual growth rate and recognize that the length of a timestep is 10 years, where we recognize that time \( t \) climate impacts depend on the model \( m \), and where a hat represents values in the absence of time \( t \) climate impacts.

It remains to describe how we calculate the integral in the conditional probability relation and how we approximate the overall density. We discretize the integral using Gaussian quadrature with \( 5^4 \) nodes.\(^1\) This quadrature scheme gives us the sampled values of \( \omega^M \) as well as the probability

\(^1\)In the plot assessing sensitivity to the choice of SSP in Section C, the short-run results for scenarios other than SSP2 use \( 4^4 \) quadrature nodes in order to reduce computational time.
weights \( p(\omega^M) \). We calculate \( p(\psi^M) \) for each value of \( \psi^M \) on a uniform grid. In the analysis where each country is its own region (which also holds GDP and population fixed at year 2010 values), we use 500\(^2\) nodes bounded in each of the two dimensions by -12 and 12. In the analysis with a single global region, we use 1000\(^2\) nodes bounded in the temperature dimension by -12 and 7 and bounded in the temperature-GDP interaction dimension by -2 and 10. These bounds do not constrain the estimated densities.

### B Step-by-Step Guide and Coefficients for Short-Run Impacts

The procedure for estimating the short-run impacts of global mean surface temperature via inter-annual variability is mostly similar, varying only in the data and in details related to estimating coefficients in heteroskedastic effects. Let \( I^S_r(T^g_t) \) be the short-run impacts on region \( r \)'s growth rate from a temperature deviation of \( T^g_t \) relative to 13.85\(^\circ\)C, a baseline temperature chosen by using the Goddard Institute for Space Studies (GISS) mean global surface temperature in 1900. Note that in this case it is the cumulative warming above this threshold that matters, not the warming over the most recent timestep or internal model warming from each model’s 1900 value. We measure cumulative warming as a deviation from 1900 to match the way temperature has been formulated in the DICE integrated assessment model. We seek the best linear estimator of the effect of \( T^g_t \) on the log of the variance, accounting for interactions with GDP per capita. We therefore seek distributions for the coefficients \( \psi \) in the following relationship:

\[
\ln \left[ \text{var} \left( I^S_r(T^g_t) \right) \right] = \psi^S_{r,T} T^g_t + \psi^S_{r,Ty} T^g_t \ln \left( \frac{y_{rt}}{y_{r0}} \right).
\]

In addition, we allow the expectation of short-run damages to evolve with temperature and GDP per capita:

\[
E \left[ I^S_r(T^g_t) \right] = \psi'_{r,T} T^g_t + \psi'_{r,Ty} T^g_t \ln \left( \frac{y_{rt}}{y_{r0}} \right).
\]

As before, we aggregate the four coefficients into a vector \( \psi^S \), and we seek the joint density function \( p(\psi^S) \). Consistent with intuition, the two coefficients in the expectation condition end up tightly clustered around zero, so we ignore them in the main text and marginalize them out in all reported results. As described below, the estimated relationships each also include a constant, which is not of interest in its own right.

Adapting the short-run specification from the third column of Table 3 in [1], which includes fixed effects and robust standard errors, for interaction effects (as described in the medium-run case), we obtain the following vector of coefficients \( \beta^S \) and covariance matrix \( \Omega^S \):

\[
\beta^S = \begin{bmatrix} -0.342 \\ -0.0118 \\ -0.0150 \\ 0.0196 \end{bmatrix},
\]

\[
\Omega^S = \begin{bmatrix} 0.0976 & -0.00373 & -0.000405 & 0.0000187 \\ -0.00373 & 0.00193 & -0.0000915 & -0.000179 \\ -0.000405 & -0.0000915 & 0.00148 & 0.0000793 \\ 0.0000187 & -0.000179 & 0.0000793 & 0.000160 \end{bmatrix}
\]
where the ordering of the coefficients is as described previously. None of these coefficients is significant at the 10% level, but the coefficient on the GDP per capita main effect (not reported) is positive and significant at the 1% level. Consistent with [1], we find that warming negatively impacts short-run growth at average GDP per capita. However, the interaction term is slightly negative and rather noisy. The interaction between GDP per capita and temperature appears more important in the medium run than in the short run.

The population-weighted, country-level, annual temperature and precipitation data and the annual global mean surface temperature all come from five simulations of CM2.5 along RCP8.5. The NOAA GFDL CM2.5 model [3] is a high-resolution GCM based on a previous lower-resolution model, CM2.1, which was widely used and analyzed in the IPCC Fourth and Fifth Assessment Reports [4]. CM2.5 has an atmosphere and land surface resolution of approximately 0.5 degrees, which is approximately 50 km in the horizontal, and an ocean resolution ranging from 28 km in the tropics to 8 km in the high latitudes. CM2.5 thus has a higher resolution than all of the available Fifth Assessment Report models used in the medium-run calculation, which have mean grid cell resolutions between 1.1 degrees and 2.8 degrees. When compared to its coarser-resolution predecessor (CM2.1), CM2.5 was shown to dramatically improve simulations of regional precipitation and climate [3, 5]. Since our analysis of country-level climate change requires averaging available grid cell precipitation and temperature, resolution becomes important for capturing regional climate change. The availability of five ensemble members allows us to explore interannual variability. The available simulations cover the years 1861–2100. The five ensemble members were generated by taking the initial conditions from a control simulation where the 1860 climate forcings are held constant and the model is left to run for several centuries. Years 101, 141, 181, 221, and 261 of the control simulation were used to initialize the five separate ensemble members. They follow the historic climate forcings from 1861-2005 and then the RCP8.5 forcings through 2100. Figure S2 plots global mean surface temperature from each of these simulations of CM2.5. All years are used when calculating the “surprising” components as described below, but only the years 2015–2100 are used as data in the impacts calculations. All data are left in annual form.

Figure S2: Global mean temperature and precipitation from each of the five simulations of CM2.5.
As discussed in the Methods, in contrast to the medium-run specification, we do not difference
the country-level temperature and precipitation data in this short-run specification. Instead, we
approximate the components of temperature and precipitation that may surprise a time \( t \) decision-
maker in country \( k \), as these surprising components are the ones omitted by the medium-run, chang-
ing averages specification. In order to separate uncertainty about future warming from weather
that is surprising conditional on global warming, we assume that agents correctly anticipate the
next year’s global mean surface temperature. Agents use a straightforward forecasting rule: a
linear projection of time \( t + 1 \) country-level temperature (or precipitation) on time \( t \) country-level
temperature (or precipitation) and on \( t + 1 \) global mean surface temperature. More complex
forecasting methods exist in both the economics and climate science literatures, but the chosen
rule is a reasonable heuristic for ordinary agents.\(^2\) Within each simulation of CM2.5, agents es-
timate the linear projection’s coefficients via an Ordinary Least Squares regression of historical
country-level temperature (or precipitation) on lagged country-level temperature (or precipitation)
and on contemporaneous global mean surface temperature. Agents use data from all previous years
to construct forecasts for the next year.

In notation, the time \( t \) agent in country \( k \) inside simulation \( m \) uses Ordinary Least Squares to
estimate the coefficients \( \gamma \) in the following relations

\[
T_{kmt} = \gamma^T T\text{km}(t-1) + \gamma^{gT} T^g_{mt} + \epsilon^T_{kmt}, \quad P_{kmt} = \gamma^P + \gamma^{kP} P\text{km}(t-1) + \gamma^{gP} T^g_{mt} + \epsilon^P_{kmt},
\]

using data observed from 1861 through time \( t \) for country \( k \) within simulation \( m \). The estimated
coefficients are consistent as long as the process generating a year’s country-level temperature (or
precipitation) from the previous year’s outcome and the current year’s global mean surface tem-
perature is covariance-stationary and ergodic for second moments \([6]\), meaning that the covariance
structure does not vary with time and the covariance between increasingly distant observations con-
verges to zero with sufficient speed. If the agent operates without knowledge of the heteroskedastic
structure of climate impacts (which we seek to estimate), then the agent might assume that the
covariance structure is indeed stationary.

The time \( t \) agent uses the estimated coefficients and knowledge of \( T_{kt}, P_{kt}, \) and \( T^g_{t+1} \) to forecast
time \( t + 1 \) country-level temperature and precipitation. Once time \( t + 1 \) country-level temperature
and precipitation are realized, the differences between the realizations and the forecasted values
(i.e., the realized forecast errors) are the variables that cause short-run impacts via the vector \( \omega^S \).
Using hats to denote the variables forecasted using time \( t \) information about country-level weather
and foresight of time \( t + 1 \) global mean surface temperature, we have the realized time \( t + 1 \) forecast
errors as

\[
\hat{T}_{km(t+1)} = T_{km(t+1)} - \hat{T}_{km(t+1)}, \quad \hat{P}_{km(t+1)} = P_{km(t+1)} - \hat{P}_{km(t+1)},
\]

where tildes denote the forecast errors. With these forecast errors in hand, we obtain short-run
impacts for each year \( t \) in each country \( k \) and simulation \( m \) via the following equation:

\[
I^S_{kmt} = \left[ \omega^T + \omega^T_y \ln (y_{kt}/9.5349) \right] \hat{T}_{kmt} + \left[ \omega^P + \omega^P_y \ln (y_{kt}/9.5349) \right] \hat{P}_{kmt},
\]

where 9.5349 is the mean of log GDP per capita in the data from \([1]\) and growth rate impacts are
measured in percentage points.

\(^2\)Section C assesses robustness to the choice of forecasting rule.
Once we obtain short-run impacts $I_{rmt}^S$ for each year $t$, each region $r$, and each CM2.5 simulation $m$, we use them to estimate the variance and expectation of $I_r^S$ as linear functions of a constant, of global mean surface temperature, of $\ln(y_{rt}/y_{r0})$, and of the interaction between global mean surface temperature and $\ln(y_{rt}/y_{r0})$. We proceed by maximum likelihood estimation with the assumption of independent, identical, normally distributed errors. This is an eight-dimensional estimation problem with $5 \times 86$ observations, and we supply analytic gradients and Hessians. The estimated covariance matrix is the inverse of the Fisher information matrix. As in the medium-run specification, we use the coefficients and covariance matrix from this estimation procedure to define the conditional probability $p(\psi_r^S | \omega_r^S)$.

As before, we calculate $p(\psi_r^S)$ for each value of $\psi_r^S$ on a uniform grid. However, we use fewer evaluation nodes in each dimension than in the medium-run specification because the short-run specification involves additional dimensions through the expectation condition as well as a more computationally intensive estimation procedure. In the analysis where each country is its own region, we use $50^4$ nodes bounded in each of the expectation moment’s dimensions by -1 and 1, bounded in the variance moment’s temperature dimension by -4 and 4, and bounded in the variance moment’s temperature-GDP interaction dimension by -2 and 2. These bounds do not constrain the estimated densities.

We provide two figures to illustrate these calculations for select sample countries. Figure S3 provides historical temperature and precipitation data for 8 sample countries from the CM2.5 model. The individual ensembles are used to calculate the forecast errors. 10-yr ensemble mean filters are shown to highlight the overall changes in temperature and precipitation over time. Figure S4 plots the forecast errors using our baseline specification, which projects temperature and precipitation using a linear projection on the historical data for that country and for global average temperature (shown in Figure S2).

C Supporting Data and Robustness Checks

This section provides supporting information, additional results, and robustness checks.

Population and income influence both short- and medium-run impacts. The top panel of Figure S5 plots the population distribution within each country, which we hold fixed over time. This distribution is used to construct the average annual temperature and precipitation variables for each country. The bottom panel plots the initial (year 2010) GDP per capita variable from the World Bank. In the absence of climate impacts, this variable grows through GDP and population projections from the Shared Socioeconomic Pathways.

Figures S6 and S7 are the analogues of Figure 2 in the main text. Whereas the main text shows the combined impacts of changing country-level temperature and precipitation, these figures isolate each channel. Figure S6 isolates the temperature channel by setting $\omega_r^M, \omega_r^M, \omega_r^S$, and $\omega_r^S$ to zero when calculating $I_{kmt}^M$ and $I_{kmt}^S$. Figure S7 isolates the precipitation channel by setting $\omega_r^T, \omega_r^T, \omega_r^T$, and $\omega_r^T$ to zero when calculating $I_{kmt}^M$ and $I_{kmt}^S$. We see that medium-run impacts are largely driven by changes in country-level temperature, with the precipitation channel typically being of small magnitude. In contrast, the precipitation channel is often as important to the variance of short-run impacts as is the temperature channel.
Figure S3: Realized CM2.5 temperature and precipitation from 1861–2100. Light colors shown for 5 individual ensembles. Dark bold lines shown for ensemble mean 10-yr digital filter. Dashed lines shown for 2015 (start of forecast).
Figure S4: Forecast errors from 2015–2100 (same units as Figure S3). Light colors shown for 5 individual ensembles. Dark bold lines shown for ensemble mean 10-yr digital filter.
Figure S5: Inputs to the analysis: the fraction of each country’s population at each gridpoint (top), and year 2010 GDP per capita in year 2000 dollars (bottom).
Figure S6: Temperature channel: As in the main text, the expected value (top) and z-score (bottom) for medium-run (left) and short-run impacts (right), except allowing climate impacts only from country-level temperature and not from precipitation. Expected medium-run impacts are expressed in percentage points, and expected short-run impacts are expressed as a percentage change in the baseline variance of economic growth.
Figure S7: Precipitation channel: As in the main text, the expected value (top) and z-score (bottom) for medium-run (left) and short-run impacts (right), except allowing climate impacts only from country-level precipitation and not from temperature. Expected medium-run impacts are expressed in percentage points, and expected short-run impacts are expressed as a percentage change in the baseline variance of economic growth.
Figure S8: The marginal distribution of the change in the growth-temperature relationship with a 1% increase in GDP per capita. Left: growth effect of a 1°C increase in average global mean temperature over a decade. Right: variance effect of a 1°C increase in global mean temperature. Greater $\eta$ implies stronger aversion to inequality of GDP per capita among countries.

Figure S8 is an analogue of Figure 3 in the main text, except plotting the estimated marginal distribution for the temperature-GDP interaction terms (i.e., plotting the marginal distributions of $\psi_{r,Ty}^{M}$ and $\psi_{r,Ty}^{S}$) rather than the estimated marginal distributions for the direct effect of global mean surface temperature. The left panel shows that increasing income per capita from its year 2010 level tends to improve the effect of warming on the medium-run growth rate. This effect is stronger when aversion to inequality is weaker (i.e., when $\eta$ is smaller). The right panel shows that increasing income per capita from its year 2010 level tends to offset the direct effect of a warmer climate in increasing the short-run variance of growth for $\eta$ between 1 and 3, tends to mimic the direct effect in being centered around zero for $\eta = 0$, and tends to quickly offset the direct effect of a warmer climate in slightly decreasing the short-run variance of growth for $\eta = 4$.

Figure S9 decomposes the effects on global growth into temperature and precipitation channels, as described above in the case of country-level impacts. It plots the marginal distributions for the effect of warming at year 2010 GDP per capita. This figure is another analogue of Figure 3 in the main text. As in the country-level case, the precipitation channel contributes only negligibly to medium-run impacts. The precipitation channel tends to reduce the short-run variability of global growth at year 2010 GDP per capita, while the temperature channel tends to increase the short-run variability of global growth at year 2010 GDP per capita.

All previous results have considered the estimated marginal distributions of variables. Figure S10 plots the contours of the joint distributions of the temperature and temperature-GDP interaction terms. In all cases, we see that more strongly negative estimates for the direct temperature effect (i.e., at year 2010 GDP per capita) accompany more strongly positive estimates for the temperature-GDP interaction term. This concordance is intuitive: for given impact pro-
Figure S9: Decomposing the marginal distribution of global climate impacts into their temperature channels (top) and precipitation channels (bottom). For year 2010 GDP per capita and using SSP2, the left panel displays the change in the growth rate of global GDP per capita due to a 1°C increase in average global mean temperature over a decade, and the right panel displays the change in the variance of the global growth rate due to a 1°C increase in global mean temperature.
Table S1: First two central moments of estimated distributions for global growth rate impacts

<table>
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<tr>
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<tr>
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<td>0.52</td>
<td>0.53</td>
<td>0.087</td>
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projections, if we estimate climate change to be relatively severe at year 2010 GDP per capita, then we also estimate the severity of climate change to diminish relatively quickly as the world becomes wealthier. Table S1 lists the first two moments of each joint distribution (not marginalizing out the expectation conditions in the case of the short-run distribution). These moments could be used when implementing these impact estimates in integrated assessment models.

The remaining figures conduct sensitivity tests. First, Figure S11 assesses sensitivity to the choice of Shared Socioeconomic Pathway (SSP). While details of distributions can differ by SSP, we see that the same basic story tends to emerge irrespective of SSP. Second, Figure S12 assesses sensitivity to the choice of timestep in the medium-run analysis. The broad story remains the same in that low levels of inequality aversion suggest neutral impacts or even benefits from greater global mean surface temperature, whereas higher levels of inequality aversion suggest that raising greater global mean surface temperature reduces economic growth. Impact estimates tend to become more negative (suggesting more harm from warming) as the timestep shortens. Also, note that shorter timesteps generate more observations for use in the regression of simulated impacts on global mean surface temperature and GDP per capita.

Third, Figure S13 assesses sensitivity of medium-run results to alternate methods and data. The left panel projects GDP per capita without adjusting for any climate impacts that happen within a model simulation. GDP per capita is thus completely exogenous rather than being affected by the value of ω^M. We see that the broad results are not sensitive to this modeling choice. The right panel uses the CM2.5 simulations in place of the CMIP5 simulations in the medium-run analysis. CM2.5 operates at a higher resolution than any of the CMIP5 models. However, there are only 5 simulations of CM2.5 as opposed to 17×4 simulations with the CMIP5 suite, and there are only 7 timesteps in the medium-run case as opposed to 86 timesteps in the short-run case. This reduction in the number of observations makes each regression estimate noisier, tending to shift each medium-run distribution close to zero. This result highlights the importance of having a suite of models for...
Figure S10: Contour plots for the joint distributions of the parameters in $\psi_r^M$ and $\psi_r^S$ under SSP2.
Figure S11: Sensitivity of global growth results to choice of SSP, at $\eta = 0$ (top) and $\eta = 2$ (bottom). For year 2010 GDP per capita, the left panels display the marginal distribution for the change in the growth rate of global GDP per capita due to a 1°C increase in average global mean temperature over a decade, and the right panels display the marginal distribution for the change in the variance of the global growth rate due to a 1°C increase in global mean temperature.
The final set of sensitivity analyses assess robustness to the manner in which agents forecast the next year’s temperature and precipitation. The forecast errors (8 sample countries shown in Figure S4) drive short-run impacts in our framework. In our baseline specification, we project temperature and precipitation using a linear projection on historical data for that country (example countries shown in Figure S3) and on global average temperature (shown in Figure S2). Figure S14 plots estimated short-run impacts when agents instead project country-level temperature and precipitation using a linear projection on only the past ten years’ worth of data (left) or when agents project country-level temperature and precipitation as the average of the past ten years’ realized outcomes (right). This figure plots the marginal distributions for the effect of global mean surface temperature at year 2010 GDP per capita, and as such is the counterpart to the short-run panel in Figure 3 in the main text. Restricting decision-makers to forecast temperature and precipitation using only the previous ten years’ worth of data does not qualitatively affect the results. Even restricting decision-makers to forecast using moving averages of the previous ten years has only a slight effect, compressing the distributions for $\eta$ equal to 1, 2, and 3 and shifting the distribution for $\eta = 4$ towards more positive values.

**D Results for Greater Inequality Aversion**

This section provides results for $\eta$ ranging from 5 to 10. Figure S15 reports the marginal distributions for the effect of warming at year 2010 GDP per capita. The medium-run results continue emphasizing more strongly negative effects as aversion to inequality ($\eta$) increases, and the short-run
Figure S13: Sensitivity analysis for the marginal distribution of global medium-run impacts. The left panel does not adjust for projected climate impacts in periods prior to \( t \) when projecting GDP per capita for period \( t \). The right panel uses data from the CM2.5 simulations (five simulations of RCP 8.5) instead of from the CMIP5 simulations (seventeen models each simulating all four RCPs).

Figure S14: Sensitivity analysis for how the process generating short-run impacts affects the estimated marginal distribution of global short-run impacts. The left panel has each year’s decision-maker forecast the next year’s country-level temperature and precipitation using only the most recent 10 years’ worth of data, and the right panel further constrains each year’s decision-maker to projecting the next year’s country-level temperature and precipitation as the average of the previous 10 years’ outcomes.
Figure S15: For higher values of $\eta$ and at year 2010 GDP per capita, the estimated distribution for the change in the growth rate of global GDP per capita due to 1°C increase in average global mean temperature over a decade (left), and the estimated distribution for the change in the variance of the global growth rate due to a 1°C increase in global mean temperature (right). Greater $\eta$ implies stronger aversion to inequality of GDP per capita among countries.

results find that warming tends to increase the interannual variability of growth for $\eta$ greater than 5, though the estimate is noisy. In all cases, increasing $\eta$ has a diminishing effect as $\eta$ reaches higher values. Finally, Figures S16 and S17 plot the joint distributions of the coefficients, and Table S2 summarizes these distributions’ expected values and covariance matrices.
Figure S16: Contour plots for the joint distributions of the parameters in $\psi_r^M$ and $\psi_r^S$ under SSP2, for $\eta$ between 5 and 7.
Figure S17: Contour plots for the joint distributions of the parameters in $\psi_r^M$ and $\psi_r^S$ under SSP2, for $\eta$ between 8 and 10.
Table S2: First two central moments of estimated distributions for global growth rate impacts, for higher values of $\eta$

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<th>$Var[\psi_{T_y}]$</th>
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References from Supplementary Information


