Climate change impacts on the within-country income distributions☆

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ABSTRACT

This paper investigates the relationship between climate change and income inequality, recognizing that the economic impacts of climate change are not uniform across different levels of income within and across countries. Using methods from the existing literature on climate and economic growth, we analyze the economic impact of rising temperatures by within-country income decile. Our findings suggest that climate change disproportionately affects the poorer segments of the population within countries, even after accounting for a country's ability to adapt to climate impacts, while richer households suffer lower damages. In the reference scenario without additional climate action (3.6°C warming), we estimate that climate impacts could lead to an increase in the Gini index by up to six percentage points, notably in Sub-Saharan Africa. We project impacts to 2100 through the RICE50+ model and estimate the income elasticity of impacts within countries. Our estimates indicate that climate change damages are regressive, with an income elasticity of damages of 0.6 under our preferred specification. On the other hand, climate benefits are approximately distribution-neutral or slightly progressive.

1. Introduction

It is widely acknowledged by the scientific community that climate change has had, and will increasingly have, significant impacts on societies and economies worldwide. Some notable examples include the impact of climate change on economic growth (Burke et al., 2015; Newell et al., 2018; Dell et al., 2012), annual income (Deryugina and Hsiang, 2014), labor productivity and supply (Graff Zivin and Neidell, 2014), human capital (Graff Zivin et al., 2018), demography (Casey et al., 2019), migration (Cattaneo et al., 2019; Desmet and Rossi-Hansberg, 2015), food security (Deschênes and Greenstone, 2007), and energy consumption (De Cian and Wing, 2019; Isaac and Van Vuuren, 2009). Impacts are expected to be heterogeneous across space and households with different income levels, occupations, and consumption patterns, among other characteristics. Such heterogeneity will thus affect the degree of inequality both within and between countries.

Between countries, climate change may exacerbate inequality (Diffenbaugh and Burke, 2019) by causing heat-related impacts that disproportionately affect low-income countries (Taconet et al., 2020). This vulnerability is generally linked to the geographic location of low-income countries in low latitudes with hotter temperatures (Mendelsohn et al., 2006).

Within countries, climate change is expected to have different effects across households. In developing countries, small-scale farmers may have limited means to adapt to climate change, for example to droughts, floods, and other disasters exacerbated by global warming (see, e.g., Cohen and Dechezleprêtre (2022) for the higher vulnerability of poorer households to mortality impacts). This vulnerability can lead to food insecurity, poverty, displacement, and to a widening economic gap between the rich and the poor. For instance, under credit constraints, temperature shocks can hinder efficient labor reallocation (Liu et al., 2023). Additionally, climate change can cause natural disasters and health risks that disproportionately affect populations already living in poverty and inequality, further exacerbating existing disparities.

However, at the global or national level, only limited evidence has been found on within-country inequality and its link to weather and climate. A few exceptions include studies focusing on Vietnam (de Laubier Longuet Marx et al., 2019) and India (Sedova et al., 2019). Therefore, the effects of temperature change on inequality within different countries remain unclear. Some studies link higher climate change vulnerability to greater inequality in developing countries, with less pronounced effects in developed ones (Cevik and Jalles, 2023), as well as increased inequality between and within communities (Hsiang et al., 2019). Preliminary evidence focusing on aggregate indexes suggests that global warming could lead to an increase in within-country inequality — as measured by the Gini index (Malpede and Percoco, 2021; Dasgupta et al., 2023; Paglialunga et al., 2022), or by the income share of the poorer half of the population, through the effects of precipitation (Palagi et al., 2022).

This study contributes to the existing literature by analyzing in a novel way the impact of climate change on income inequality within countries. Unlike previous studies such as Diffenbaugh and Burke (2019), which focus on between-country inequality, we provide an explicit and direct measure of income inequality *within* countries across income deciles. We estimate three different climate impact functions, using decile-level economic data and country-level climate data, to study the economic consequences of climate change on the within-country income distribution.[1]

Results show that the distributional consequences of climate impacts are regressive within countries, consistently for all three damage function specifications (although the choice of damage function strongly influences global projected impacts). Specifically, the poorest individuals within countries (those in the first decile of the income distribution) are projected to suffer the most severe economic impacts of climate change. Additionally, the vulnerability to rising temperatures decreases almost monotonically across income deciles within countries. Moreover, in line with the existing literature, the majority of climate damages is concentrated in the hotter and poorer regions of the world: those most affected by climate change are the poorest *between* and *within countries*. Allowing for income-based adaptation, population-weighted within-country variation of climate damages accounts for almost two-thirds of the variance of total damages by 2100, with the remaining variation explained by variation in damages across countries.

The global within-country income elasticity of damages and benefits is a summary statistic providing a simple quantification of the distributional implications of climate impacts. It can be used as input for other assessments, e.g., for the Social Cost of Carbon (Dennig et al., 2015). This value is estimated with an extensive Monte Carlo analysis, resulting in a central value of 0.64 and a 25/75% confidence range of [0.5;0.8] for the elasticity of damages, and a central value of 1.01 [0.8;1.2] for the elasticity of benefits. Climate change damages are more regressively distributed in poorer and warmer countries, while benefits are captured slightly more by the richer deciles in advanced economies.

The article is organized as follows. Section 2 presents the empirical strategy estimating the impact functions by income decile. After describing the data in Section 3, Section 4 presents the results. The following sections discuss the projected damages until 2100 (Section 5) and the income elasticity of climate impacts (Section 6), followed by the conclusions in Section 7.

2. Empirical strategy

The empirical strategy employs three different impact functions from the climate econometrics literature to study the effect of weather variables (annual temperature and precipitation) on the growth of income across income deciles within countries. Given the existing uncertainty regarding the most appropriate specification and the importance for climate damage projections, as highlighted in Newell et al. (2021), we consider multiple impact functions specification. These three impact functions build on Burke et al. (2015), Kalkuhl and Wenz (2020) and Jiao et al. (2023), respectively. We estimate them separately for each decile $q = 1, \ldots, 10$ of the (within-country) net income distribution. We model the income growth of each decile as a function of annual mean temperature, cumulative yearly precipitation, and other covariates, which include the usual fixed effects by country and year, as well as country-specific trends. We further include among the covariates one lag of the dependent variable, as in Pretis et al. (2018), to better account for the dynamics of income by decile and better isolate the effects of temperature. Note that with the large time dimension in our data ($T \approx 55$), the bias on the lagged dependent variable coefficient in fixed effect models becomes negligible.

The impact function from Burke et al. (2015) (henceforth BHM) allows for a non-linear relation between temperature and output growth through the use of quadratic terms so that a marginal increase in temperature may have a differential effect in countries with different climates. At the same time, this specification implicitly assumes that countries' response to temperature changes only depends on their initial temperature levels and not on other factors. Formally:

$$\Delta y_{it}^q = \Delta y_{it-1}^q + \beta_1^q Temp_{it} + \beta_2^q Temp_{it}^2 + \gamma_1^q Prec_{it} + \gamma_2^q Prec_{it}^2 + \alpha_i + \theta_t + \zeta_i t + \zeta_i t^2 + \epsilon_{it} \qquad (1)$$

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[1] We estimate the impact functions of Burke et al. (2015), Kalkuhl and Wenz (2020), and Jiao et al. (2023), as detailed below.

with i and t indexing country and year, respectively. y_{it} is the real per capita income of decile q in logarithm. Δ is the first-difference operator, $Temp_{it}$ is the annual average temperature, and $Prec_{it}$ is annual cumulative precipitation,[2] α_i and θ_t are country- and year-fixed effects, $\zeta_i t$ and $\zeta_i t^2$ are linear and quadratic country-specific time trends.

The impact function from Kalkuhl and Wenz (2020)[3] (henceforth KW) for the decile q is:

$$
\begin{aligned}
\Delta y_{it}^q = {} & \Delta y_{it-1}^q + \beta_0^q \Delta Temp_{it} + \beta_1^q \Delta Temp_{it-1} + \beta_2^q \Delta Temp_{it} * Temp_{it-1} + \beta_3^q \Delta Temp_{it-1} * Temp_{it-1} \\
& + \lambda_0^q \Delta Prec_{it} + \lambda_1^q \Delta Prec_{it-1} + \lambda_2^q \Delta Prec_{it} * Prec_{it-1} + \lambda_3^q \Delta Prec_{it-1} * Prec_{it-1} \\
& + \phi_1^q Prec_{it-1} + \phi_2^q Prec_{it-1}^2 + \zeta_1^q Temp_{it-1} + \zeta_2^q Temp_{it-1}^2 + \alpha_i + \theta_t + \delta_i t + \epsilon_{it}
\end{aligned} \tag{2}
$$

As in BHM, this modeling choice allows for heterogeneous impacts of temperature shocks across different climates without additional forms of heterogeneity. Moreover, it allows weather variables to have both a *level effect* on aggregate output from the terms in first difference (i.e. a temporary effect on the growth rate of output) and a *growth effect* from the terms in levels (i.e. a permanent effect on the growth rate of output).

Next, we consider the possibility that income alters the responsiveness of growth to the local climate, as in Jiao et al. (2023).[4] By observing damages from temperature shocks, we can infer that adaptation to climate shocks is costly. Higher income relaxes the budget constraint under which economic agents undertake the optimal adaptation decision. Hence, the wealthier an agent is, the more they can invest in adaptation to insulate themselves from climate impacts. This simple theoretical hypothesis guides the empirical specification of the impact function, which allows for income-driven adaptation. In an extension of Burke et al. (2015), we interact each term of the quadratic functions of temperature and precipitations with y_{it-1}, the lagged country-level log of GDP per capita of country i. This can capture private adaptive capacity, allowing investment into proactive or reactive adaptation measures, but also public adaptation measures. We refer to this model specification as BHM-Adaptation. This is our preferred specification and the one we focus on when presenting our main results in Sections 4 and 5, while showing that the main takeaways regarding the distributional consequences of projected climate impacts are robust to the choice of the damage function.

$$
\begin{aligned}
\Delta y_{it}^q = {} & \Delta y_{it-1}^q + Temp_{it}(\beta_1^q + \beta_3^q y_{t-1}) + Temp_{it}^2(\beta_2^q + \beta_4^q y_{t-1}) + Prec_{it}(\gamma_1^q + \gamma_3^q y_{t-1}) \\
& + Prec_{it}^2(\gamma_2^q + \gamma_4^q y_{t-1}) + \alpha_i + \lambda_t + \delta_i t + \epsilon_{it}
\end{aligned} \tag{3}
$$

The hypothesis is that income mitigates damages caused by deviations from the optimal temperature, and we expect that β_3 and β_4 have opposite signs to β_1 and β_2, respectively. Given that GDP per capita is always positive, the higher a country's average income is, the flatter its temperature response function will be, and vice versa.

Hence, this reduced-form specification can capture, for example, the kind of adaptation that takes place by re-allocating production to sectors less exposed to the higher temperature's negative impacts on productivity (see *e.g.* Somanathan et al. (2021)), or by investing in protective technologies such as air conditioning (Barreca et al., 2015). This extension of the polynomial damage function specification allowing for income-driven adaptation follows (Carleton et al., 2022), who apply a similar strategy to the mortality impacts of daily temperatures.[5] Jiao et al. (2023) show how outlier observations in the dependent variable of interest can distort OLS coefficients because some identifying variation in the dependent variable may be erroneously attributed to variation in the climate variables of interest, thus biasing the coefficients on those variables, despite the presence of fixed effects and other controls. Because of this, we present in Section A.1 results for the decile-level BHM-adaptation damage function estimated with OLS dropping the top and bottom 1% of outliers, as well as using the Impulse Indicator Saturation (IIS) estimator proposed in Santos et al. (2008). The sign and size of the coefficients are robust, but come at a cost in precision, especially for the lower deciles, leading us to rely on the full-sample results when presenting the projected distributional consequences of climate impacts.

In addition to the decile-level damage functions, we estimate the country-level corresponding functions, with the same explanatory variables and where the dependent variable is Δy_{it}, the growth of real per capita GDP in country i and year t.

To summarize, we estimate a separate set of coefficients for each income decile. We evaluate how the ten deciles of net income distribution respond to the same country-level variations in annual temperature. The distributional consequences of climate change within each country will then depend on the relative slopes of the impact function among each decile. Income inequality will worsen due to climate change if the impact functions for lower deciles, evaluated at the country's current climate, have a steeper negative slope than the upper deciles of the income distribution, and vice versa. When presenting our decile-level results on the impact of temperatures on decile income growth in Sections 4 and 5, we focus especially on the findings from the estimation of Eq. (3). In Section 6 we show that our main findings on the distribution of climate impacts within countries hold across all three impact function specifications from the literature.

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[2] Whereas Kotz et al. (2022) also include extreme indices of climate in the framework of Kalkuhl and Wenz (2020), their results suggest that the largest part of impacts can indeed be captured by annual mean temperature. Hence we focus on these aggregate values here.

[3] We consider column (5) from Table 4 in Kalkuhl and Wenz (2020), as this is indicated as the preferred panel specification in the paper and the one used for climate impact projections

[4] A similar specification is also examined in Burke et al. (2015), Extended Data figure 1, but with an interaction for the linear temperature term only.

[5] We show in Section A.1 that our results are robust to considering the average per capita GDP over the sample period, a rolling average of 10 or 15 years for $\bar{y}_i$, as well as to excluding precipitation controls or allowing for quadratic trends.

Table 1
Summary statistics.

	Name	Mean	Min	Max	SD
1	Log(GDP pc)	8.20	5.11	11.63	1.43
2	GDP pc growth	0.02	−1.03	0.68	0.06
3	1st decile, share in %	2.21	0.00	5.36	0.98
4	2nd decile	3.66	0.18	7.21	1.30
5	3rd decile	4.67	0.21	8.07	1.40
6	4th decile	5.66	0.56	8.96	1.42
7	5th decile	6.71	1.58	9.82	1.38
8	6th decile	7.92	2.44	10.78	1.29
9	7th decile	9.47	4.05	12.50	1.11
10	8th decile	11.66	6.17	14.64	0.83
11	9th decile	15.41	10.85	19.49	0.86
12	10th decile	32.70	13.74	70.95	8.89
13	Annual temperature (°C)	18.02	−3.47	29.98	7.68
14	Annual precipitation (mm)	91.22	0.83	356.52	55.93

3. Data

Temperature and precipitation data come from the Climate Research Unit at the University of East Anglia. We aggregate gridded monthly average temperature and precipitation with 0.5° resolution using population weights at the same resolution from the SocioEconomic Data and Applications Center (SEDAC) at Columbia University, accounting for cells that are only partially covered by a country's borders and for the area extent of each pixel. This is done computing the weights w for each grid cell belonging to a country according to the formula $w_{j,i} = c_{j,i} * a_{j,i} * p_{j,i}$, where c_i is the fraction of the cell j that falls within country i's borders, $a_{j,i}$ is the area in km covered by the grid-cell (this changes across latitudes) and $p_{j,i}$ is the population count/km in the cell. The monthly series are then aggregated to the annual level in order to match the macroeconomic indicators.

GDP growth data comes from World Bank's Development Indicators, calculated from GDP per capita in constant 2015 USD. Decile-level income is reconstructed from decile-level income shares data described and assembled in Narayan et al. (2023b) and slightly updated in Narayan et al. (2023a). The authors combine publicly available data on the deciles of the within-country distribution of net income (post-tax, disposable) from the UNU Wider World Income Inequality Database (WIID), with data on deciles for consumption, and country-level Gini data from the World Bank's World Development Indicators. Briefly, they impute the missing values for income deciles with the predicted values coming from (i) consumption data when available (predicted through OLS), and (ii) Gini data through Principal Component Analysis. This yields an almost balanced panel dataset, in contrast to a strongly unbalanced WIID. We compute decile-level income levels multiplying decile-level income share by GDP per capita. The analysis is performed on unbalanced data (because of missing Gini or GDP data) from 1960 to 2015. Table 1 presents the summary statistics of the variables we use for our empirical specifications.

Projections follow the combined Shared Socioeconomic Pathways (SSPs) for country-level socioeconomic variables (Population and GDP) (Riahi et al., 2017). We use as a reference the SSP3 scenario, which follows current trends in regional rivalries and conflicts, assuming reversal in globalization trends (O'Neill et al., 2017). SSP2 is explored as a robustness check (see Section A.5). We compare this scenario without climate impacts to the same projected per-capita GDP after applying climate impacts from temperature increases. The impacts are based on the damage coefficients estimated in Section 4. Since the regression coefficients for precipitation are imprecisely estimated and its future projections are not reliable, we focus our analysis on the effects of temperature, in line with the existing literature.

To create our baseline scenario under SSP3 with no climate impacts, we use the RICE50+ model, described in detail in Gazzotti (2022). The model is an extension of Nordhaus's seminal DICE model (Nordhaus, 2017) and features 154 countries. Temperature is downscaled to the country level based on the CMIP6 model ensemble (Eyring et al., 2016). The model includes projections for total GDP and population at the country level as well as projections on decile-level income, depending on the SSP scenario. The main scenario we consider when presenting our results sees GDP growing under the SSP3 scenario, thus yielding temperatures similar to the high-emission RCP 7.0 scenario. Indeed, the global average increase in surface temperature is around 3.6 °C by 2100 under this scenario relative to preindustrial (Appendix Figure A.5).

4. Empirical results

Estimates from Eq. (3) (BHM-Adaptation) confirm that country-level income plays a crucial role in reducing vulnerability to climate damages. In addition, the poorer deciles are more affected by climate, furthering within-country inequalities. The estimated coefficients are presented in Table 2.

Notably, two key factors contribute to larger damages in lower-income countries. First, the damage function of lower-income countries exhibits a steeper curve. This implies that marginal damages grow faster in poorer countries as temperatures deviate from the optimal level in a warming world. An inverted-U damage function, consistently with previous studies (e.g., Burke et al. (2015)), becomes less pronounced as GDP increases. This reduced sensitivity of economic growth between countries results from

Table 2

Damage functions, with BHM-adaptation.

Dependent variables:	Decile income growth										GDP pc growth
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Temperature	0.1657***	0.1390***	0.1375***	0.1356***	0.1304***	0.1281***	0.1275***	0.1288***	0.1278***	0.1180***	0.1329***
	(0.0621)	(0.0399)	(0.0352)	(0.0317)	(0.0287)	(0.0268)	(0.0252)	(0.0238)	(0.0227)	(0.0237)	(0.0237)
Temperature, Squared	−0.0045**	−0.0032**	−0.0033***	−0.0033***	−0.0032***	−0.0031***	−0.0031***	−0.0031***	−0.0031***	−0.0028***	−0.0032***
	(0.0021)	(0.0014)	(0.0012)	(0.0011)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Temperature × GDP($t-1$)	−0.0152**	−0.0124***	−0.0126***	−0.0124***	−0.0122***	−0.0120***	−0.0120***	−0.0122***	−0.0121***	−0.0107***	−0.0126***
	(0.0063)	(0.0040)	(0.0036)	(0.0032)	(0.0030)	(0.0028)	(0.0026)	(0.0025)	(0.0024)	(0.0026)	(0.0025)
Temperature Sq. × GDP($t-1$)	0.0004*	0.0003*	0.0003**	0.0003**	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(9.43×10^{-5})	(8.9×10^{-5})	(8.59×10^{-5})	(9.57×10^{-5})	(8.81×10^{-5})
Fixed-effects											
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Varying Slopes											
Year (Country)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics											
Observations	5,551	5,551	5,551	5,551	5,551	5,551	5,551	5,551	5,551	5,551	5,551
R²	0.09430	0.09704	0.10928	0.13340	0.16973	0.20311	0.24298	0.27602	0.27332	0.14926	0.30600
Within R²	0.06357	0.02177	0.02327	0.03068	0.03692	0.04902	0.06888	0.08896	0.08365	0.04845	0.11574

Clustered (Country) standard-errors in parentheses.

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Note: Regressions of decile income growth (columns 1 through 10) and GDP per capita growth (column 11) on a function of temperature and income. All regressions also include precipitation, squared precipitation, and their interaction with lagged income levels.

the interaction terms of lagged income with linear and quadratic temperature, with these terms exhibiting opposite signs of the non-interacted temperature terms for all deciles. To illustrate this, Fig. 1 displays the decile-level and country-level damage functions at various income levels for a hypothetical low-income country (25th percentile of per capita GDP observations in the sample, 1300 USD), a middle-income country (50th percentile, 3463 USD), and a high-income country (75th percentile, 12968 USD). Confidence intervals are excluded in the figure for visual clarity, and they are reported in Figure A.2 in the Appendix. Results do not appear to be artifacts of the reconstruction of income shares in Narayan et al. (2023a) (Section A.1 in Appendix).

Second, current temperatures are already further above the optimal temperature in poorer countries than they are in richer ones. The optimal temperature estimated from the decile-level regressions across income levels of countries is around 18 °C (although it varies slightly across deciles), higher than the optimal levels of Burke et al. (2015) (13 °C) and Kalkuhl and Wenz (2020) (5 °C). Low-income countries are on average warmer meaning that, assuming a quadratic damage functions, a marginal increase in temperatures leads to proportionally larger losses in output growth.

The impacts are also unequal within countries. As plotted in Fig. 1 and implied by the coefficients of Table 2, the damage functions show that the income of poorer households is more responsive to temperature changes regardless of GDP levels. In addition to this, we also see that the responsiveness to temperature appears to decrease almost monotonically across income deciles.

To summarize, the sensitivity of income to climate decreases along the income distribution both between and within countries. The within variation is the key result underpinning Sections 5 and 6 on the distributional consequences of climate change impacts.

5. Projected distributional impacts

The previous section highlighted the distributional effects of climate change estimated over the past half-century, within and between countries. However, it remains unclear what the future distributional implications will be. On the one hand, increasing temperatures will damage GDP growth; on the other hand, higher income levels will increase adaptive capacity. We, therefore, project damages to the end of the century and explore the distributional implications within and between countries.

We project GDP and temperature using the RICE50+ model (Gazzotti, 2022). Decile-level income is reconstructed from projected decile shares (Narayan et al., 2023b) and GDP. Impacts for each decile q in time t are then defined as the difference between the projected income per capita y_{it}^q with climate impacts and counterfactual income per capita $\widetilde{y}_{it}^q$ without impacts[6]:

$$d_{it}^q = \widetilde{y}_{it}^q - y_{it}^q. \tag{4}$$

The counterfactual $\widetilde{y}_{it}^q$ is constructed letting income of decile q in year t and country i evolve according to:

$$\widetilde{y}_{it}^q = (1 + g_{it}^q)\widetilde{y}_{it-1}^q \tag{5}$$

where g is the counterfactual growth rate under no climate impacts from the SSPs. Income with climate impacts is

$$y_{it}^q = (1 + g_{it}^q + \delta_{it}^q)y_{it-1}^q \tag{6}$$

with δ_{it}^q is the estimated climate impact factor, which differs across impact function specifications. It represents the reduction or increase in economic growth rate caused by deviations from the optimal temperature. Under the BHM specification, δ_{it}^q is:

$$\delta_{it}^{q,BHM} = \widehat{\beta_1}^q(Temp_{it} - Temp_{i0}) + \widehat{\beta_2}^q(Temp_{it}^2 - Temp_{i0}^2) \tag{7}$$

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[6] Analogously, country-level damages are defined as $\sum_q d_{it}^q = \sum_q (\widetilde{y}_{it}^q - y_{it}^q)$.

Decile-level damage functions, with BHM-adaptation

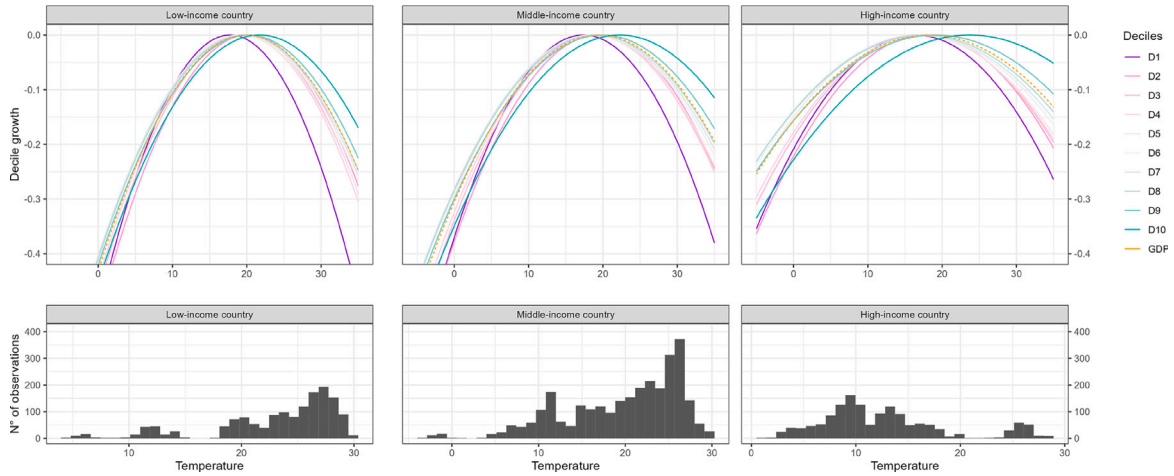Function varies by income level of the country

Fig. 1. Damage functions at the decile level. *D1* to *D10* indicate deciles from the poorest to the richest. *GDP* indicates the country-level damage functions. Decile-level damage functions with income-driven adaptation for three selected countries at different income levels. The shape of the function varies with the income level both within and between countries. Confidence intervals have been omitted for visual clarity; they are reported in Figure A.2 in the Appendix. *Low income*: 25th percentile of the GDP per capita distribution in the sample, 1,300 USD per capita. *Middle income*: 50th percentile, 3,463 USD. *High income*: 75th percentile, 12,968 USD.

Under the KW specification, it is:

$$\delta_{it}^{q,KW} = \widehat{\beta_0}^q \Delta Temp_{it} + \widehat{\beta_1}^q \Delta Temp_{it-1} + \widehat{\beta_2}^q \Delta Temp_{it} * Temp_{it-1} + \widehat{\beta_3}^q \Delta Temp_{it-1} * Temp_{it-1} \tag{8}$$

Under the BHM-Adaptation specification, it is:

$$\delta_{it}^{q,BHM-Adaptation} = (Temp_{it} - Temp_{i0})(\widehat{\beta_1}^q + \widehat{\beta_3}^q y_{it-1}) + (Temp_{it}^2 - Temp_{i0}^2)(\widehat{\beta_2}^q + \widehat{\beta_4}^q y_{it-1}) \tag{9}$$

where $Temp_{i0}$ is temperature in country i in 2015 and y_{it-1} is the lagged GDP per capita under climate impacts in logarithms. Note the compounding of effects: climate change may reduce income levels and thus the ability to adapt, causing larger relative damages.

The projected impacts across damage functions are of the same order of magnitude. In 2100, under a RCP 7.0 warming scenario, global impacts on per capita GDP are projected at around 9% of GDP under the BHM specification, 7.5% under the BHM-Adaptation specification and about 2.4% of GDP under the KW specification (when estimated with country-level data instead of the original sub-national level data).[7] We report the estimated global impacts over time for all damage function specifications, as implied by our empirical results, in Figure A.6 in Section A.6, where we also explain some discrepancies with previous results on global projected impacts.

Distributional effects are shown by Fig. 2 , which displays projected climate impacts as a share of income across income deciles under the BHM-Adaptation specification. Median impacts are negative and similar for all deciles but the richest one. However, the impacts range and variance across countries is larger for the lower deciles. The negative and regressive effect of climate change is consistent across the three damage functions (Figures A.8 and A.9 in Appendix).

Globally, climate impacts are more regressive in hotter and poorer countries. Fig. 3 displays how the projected regressive damages vary across countries. Panel (a) plots the difference between the relative impacts (impacts as a share of income) of the lowest and the highest decile. Hence, a higher value implies that poorer strata are more exposed to climate impacts.[8] In other words, the more strongly regressive consequences will come in the currently hotter and poorer parts of the world, as implied by Fig. 1. The impact gap between the top and bottom decile is especially marked in Sub-Saharan Africa, the Middle East, South Asia, as well as parts of Latin America.

Fig. 3b displays the consequences for the Gini index by country of our projected decile-level climate impacts under the SSP3 scenario, implying warming of +3.6 °C by 2100. Consistently with the findings in panel (a), higher starting temperatures are projected to increase within-country inequality, as measured by the Gini index, for basically every country in the world. The stronger negative consequences for an equal distribution of income within countries are again projected to be seen in Sub-Saharan Africa and the Middle East, with a projected increase of up to 6 points in the index. This is broadly consistent with the previous findings in Malpede and Percoco (2021), Paglialunga et al. (2022) and Cevik and Jalles (2023), despite the different econometric models used.

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[7] In Figure A.11 in Section A.8, we display projected damages across four SSP-RCP scenarios for all three damage functions.

[8] in Figure A.7 in Section A.7 we display projected damages in 2100 to per capita income for all deciles in all countries, for completeness
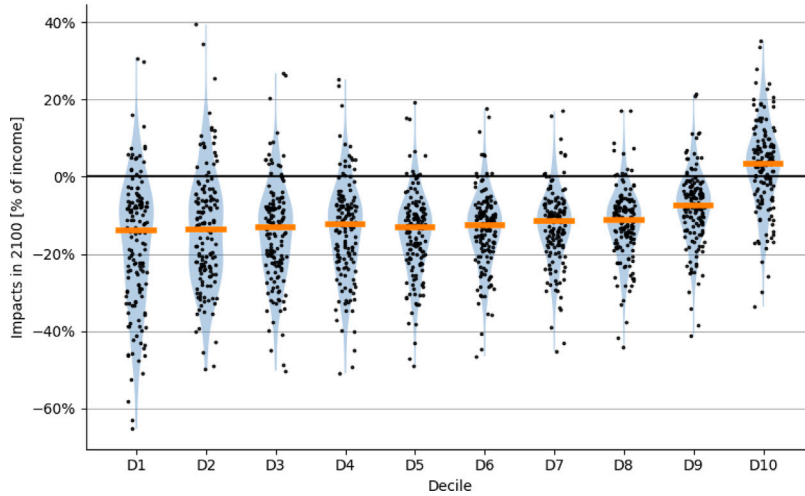
Fig. 2. Projected decile-level impacts in 2100 under SSP3 scenario, with a climate sensitivity equal to 1. Each dot represents the projected impact on decile-level income for a given income decile in one of the 154 countries of RICE50+. Dot placement is slightly perturbed for visualization purposes. Horizontal orange lines mark the medians of the distribution, for each decile, of projected impacts across regions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
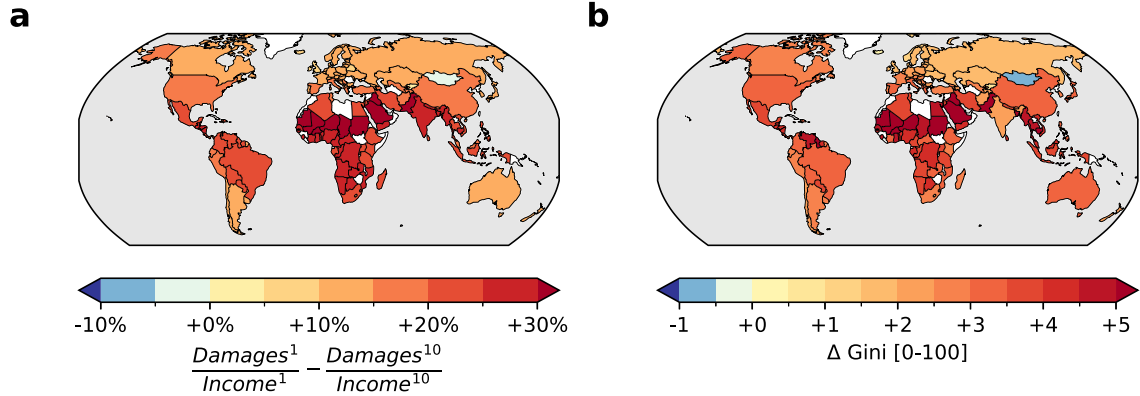

Fig. 3. Distributional effects of climate damages by 2100 under SSP3 and BHM-Adapt damages. Panel (a): differences in damages as a share of income between D1 and D10. Panel (b): impact of climate change on the Gini index.

Therefore, climate change is estimated to have adverse distributional consequences in the future, globally worsening within-country inequality across the century. The next section estimates the income elasticity of climate impacts to provide a summary measure for this effect.

6. The income elasticity of climate impacts

The income elasticity of climate impacts – how responsive relative damages are to a change in income along the within-country income distribution – has important implications for poverty, for political economy considerations, and, ultimately, for the socially optimal climate policy and the Social Cost of Carbon (Dennig et al., 2015). The income elasticity ξ is defined by the relationship

$$d_{it}^q \propto \left(\widetilde{y}_{it}^q\right)^\xi . \tag{10}$$

Impacts are proportional to income (*i.e.*, distribution-neutral) if $\xi = 1$, and fall disproportionately on the poor when $\xi < 1$ and on the rich when $\xi > 1$.

We estimate the within-country income elasticity of climate impacts until 2100 using a standard log–log regression of decile-based impacts on per capita income level (Eqs. (11) and (12)). We use a fixed effects model, whereby we include a full set of country-year fixed effects. This allows us to identify the elasticity relying on variation within a country-year combination.

Some countries and deciles could experience benefits from higher temperatures if their climates start from a temperature to the left of the estimated optimal temperature. Therefore, climate impacts can be both positive (i.e. benefits) or negative (i.e. damages).

Table 3
Income elasticity of climate impacts.

	Damages			Benefits		
	BHM-Adapt	BHM	KW	BHM-Adapt	BHM	KW
Mean estimate	0.64	0.76	0.60	1.01	1.15	1.13
Full uncertainty IQR	[0.51, 0.75]	[0.63, 0.83]	[0.53, 0.61]	[0.78, 1.21]	[0.86, 1.34]	[0.91, 1.29]
Full uncertainty 95% range	[0.37, 1.11]	[0.51, 1.43]	[0.45, 1.18]	[0.46, 1.73]	[0.64, 2.22]	[0.72, 1.9]
Econometric uncertainty σ	0.22	0.26	0.17	0.32	0.44	0.29
Climate uncertainty σ	0.07	0.07	0.03	0.26	0.19	0.18
Full uncertainty σ	0.20	0.22	0.16	0.34	0.40	0.30

Within-country income elasticity of climate impacts under SSP3 from the Monte Carlo analysis. Temperature is projected, drawing 500 climate sensitivities from a *Lognormal*(1.1, 0.3), while 500 damage function parameters are drawn from empirical multivariate normal distributions characterized by the covariance estimated in Section 4. *Mean estimate* are averages across all simulations, encompassing both climate model and statistical uncertainty. The *Full uncertainty IQR* and *Full uncertainty 95% range* indicate the interquartile range (IQR) and the 95% coverage range across all simulations, encompassing both climate model and statistical uncertainty. The *Econometric uncertainty σ* indicates the standard deviation of the within-country income elasticity of climate impacts across Monte Carlo simulations in which the climate sensitivity is fixed at 3. The *Climate uncertainty σ* indicates the standard deviation of the within-country income elasticity of climate impacts across Monte Carlo simulations in which damage function parameters are fixed at point estimates. The *Full uncertainty σ* is the uncertainty from the full set of Monte Carlo results.

To estimate a meaningful income elasticity, we split the data and separately estimate the income elasticity of damages (ξ^-) and the income elasticity of benefits (ξ^+) according to:

$$ln\left(-d_{it}^{q-}\right) = \alpha_i^- + \xi^- ln\left(\widetilde{y_{it}^q}\right) + \phi_{it}^- + \epsilon_{it}^{q-} \tag{11}$$

$$ln\left(d_{it}^{q+}\right) = \alpha_i^+ + \xi^+ ln\left(\widetilde{y_{it}^q}\right) + \phi_{it}^+ + \epsilon_{it}^{q+} \tag{12}$$

Here, d^{q-} are climate damages and d^{q+} are climate benefits, $\phi_{it}^{\cdot}$ denotes a set of country-year fixed effects and $\epsilon_{it}^{q\cdot}$ a random error term.

Both elasticities imply progressivity of impacts for values greater than 1 and regressivity for values smaller than 1. It should be noted, however, that $\xi^+ > 1$ is progressive from a mathematical perspective, but otherwise *socially* regressive: benefits are disproportionately enjoyed by the wealthier deciles.[9]

To better characterize the evolution of climate impacts, we explore the climate model and econometric uncertainty with a Monte Carlo simulation. To explore climate uncertainty, we simulate climate trajectories under different equilibrium climate sensitivities (ECS). We draw 500 climate sensitivities from a *Lognormal*(1.1, 0.3), which has a 66% (17%–83%) range for sensitivity of 2.2-3.9 K per doubling of atmospheric carbon dioxide, in line with the current understanding of the ECS (Sherwood et al., 2020). Given the climate sensitivity, we reconstruct a global temperature projection using the climate module within RICE50+ (Figure A.5). The RICE50+ climate module is a three-layer carbon and two-layer temperature model, adjusted in its exchange coefficients to match the MAGICC6 model emulation (Meinshausen et al., 2011). The econometric uncertainty is derived drawing at random 500 values from a multivariate normal distribution with the covariance estimated in Section 4. Finally, for each specification (drawn from the parameter space) and temperature projection, we reconstruct the evolution of income with impacts y_{it}^q and d_{it}^q. That is, we compute 250,000 elasticities for each damage function and for each SSP scenario. Results for SSP2 are similar and shown in the Appendix.

Fig. 4 shows the distribution of within-country income elasticities, and Table 3 provides summary statistics. While global projected damages are sensitive to the choice of the damage function as shown in Newell et al. (2021) and in Figure A.6, the income elasticity of climate impacts is consistent across the three specifications. The damages from climate change are projected to be disproportionately borne by poorer deciles. The mean income elasticity of damages is estimated at 0.64 under BHM-Adaptation, 0.76 under the BHM specification, and 0.60 under the KW specification, with the 75th percentile of the distribution substantially below 1 for all specifications. The income elasticity of climate benefits has a comparatively wider distribution, the central estimate of which is close to distribution neutrality. The mean estimate of ξ^+ is 1.01 for BHM-Adaptation, 1.15 for BHM, and 1.13 for KW.

The existing literature offers some, yet limited, comparisons. Mendelsohn et al. (2012) find an income elasticity of 0.42 for damages from tropical cyclones. For some impacts, the elasticity could even be negative (Tol, 2021), while an average elasticity of damages of 1 (proportional damages) has also been used (Anthoff and Tol, 2012; Dietz et al., 2018). Therefore, our results fall within a range that is compatible with previous work on the topic.

We then explore heterogeneity in elasticities above and below median GDP in Table 4, and above and below median temperatures. Projections use the point estimates of Eq. (3) and temperature projections with an ECS of 3. Damages are more regressive in poorer countries (those with a below-median per capita GDP, $\xi^- = 0.51$) as well as in hotter countries (those with above median annual temperature, $\xi^- = 0.47$). Benefits are more disproportionally enjoyed by the higher deciles in richer ($\xi^+ = 1.43$) and warmer

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[9] Dennig et al. (2015) use a slightly different definition of relative terms writing $\frac{d_{it}^q}{d_{it}} = a_i \left(\frac{\widetilde{y_{it}^q}}{\widetilde{y_{it}}}\right)^\xi$. While we could estimate this equation based on decile shares without fixed effects and identify within-country effects, the results are slightly different due to the non-linear transformation. In addition, the relative terms formulation raises questions on how to deal with climate benefits, not originally considered in Dennig et al. (2015). We thank an anonymous referee for pointing us to the differences between the two definitions.
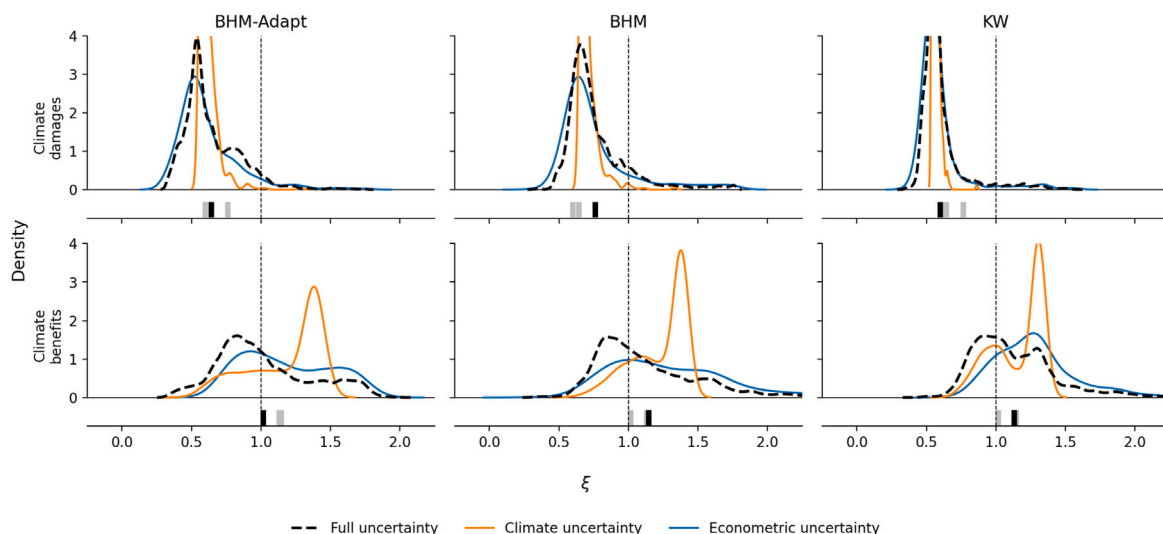
Fig. 4. Distribution of the within-country income elasticity of climate impacts under SSP3 from the Monte Carlo analysis. Temperature is projected, drawing 500 climate sensitivities from a *Lognormal*(1.1, 0.3), while 500 damage function parameters are drawn from empirical multivariate normal distributions characterized by the covariance estimated in Section 4. *Full uncertainty* is the uncertainty from the full set of Monte Carlo results. *Climate uncertainty* is the uncertainty stemming from the variation in climate sensitivity. *Econometric uncertainty* is the uncertainty from the damage function parameters. Vertical black bars indicate the average values; gray bars indicate the average values of other specifications for reference. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Heterogeneity in income elasticity of climate impacts, under the BHM-Adaptation specification.

	Log(Impacts)							
	Damages				Benefits			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	< median GDP	> median GDP	< median temp.	> median temp.	< median GDP	> median GDP	< median temp.	> median temp.
Log(Income)	0.51***	0.68***	0.87***	0.47***	1.29***	1.43***	1.37***	2.85***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.10)
Country-Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10 413	9424	7636	12 201	2167	3156	4944	379
R^2	0.62	0.30	0.38	0.55	0.71	0.55	0.60	0.96
Adjusted R^2	0.62	0.30	0.38	0.55	0.71	0.55	0.60	0.96

Income elasticity of climate impacts using point estimates of BHM-Adaptation and standard temperature projections. HC3 standard errors in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

($\xi^+ = 2.85$) countries, although we suggest caution in the interpretation of the latter figure as only few deciles in warm countries experience climate benefits.

The heterogeneity of climate impacts can be further unpacked, by decomposing the variance of the projected impacts at the decile-country level in 2100. About 60% of the population-weighted variance of climate damages (in per capita terms) happens within countries, while the remainder happens between them. Conversely, only about a fourth of the population-weighted variance of climate benefits happens within countries. Fig. 5 visually explore the decomposition. The lower Panel (C) compares projected relative damages $\frac{d^q}{\sum_q d^q}$ for all decile-country observations in 2100 (that is, ten observations per country) against relative income $\frac{y^q}{\sum_q y^q}$, after removing year fixed effects. Panel (A) highlights the within-country comparison, after removing country-year fixed effects. Panel (B) aggregates damages and income to depict the variation in impacts across countries.

7. Conclusion

The results consistently show that climate change will increase within-country inequality. We first empirically investigate how temperature affects decile-level income, finding that the sensitivity of income to climate decreases along the income distribution, both between and within countries. We employ three different damage functions, with our preferred specification allowing for income-led adaptation. Second, we project future climate impacts and find that damages fall, within countries, more heavily on the poorest deciles. Third, the distributional implications of climate impacts are summarized by the income elasticities of climate damages and benefits. The central estimates imply regressive climate damages, while climate benefits are distribution-neutral or
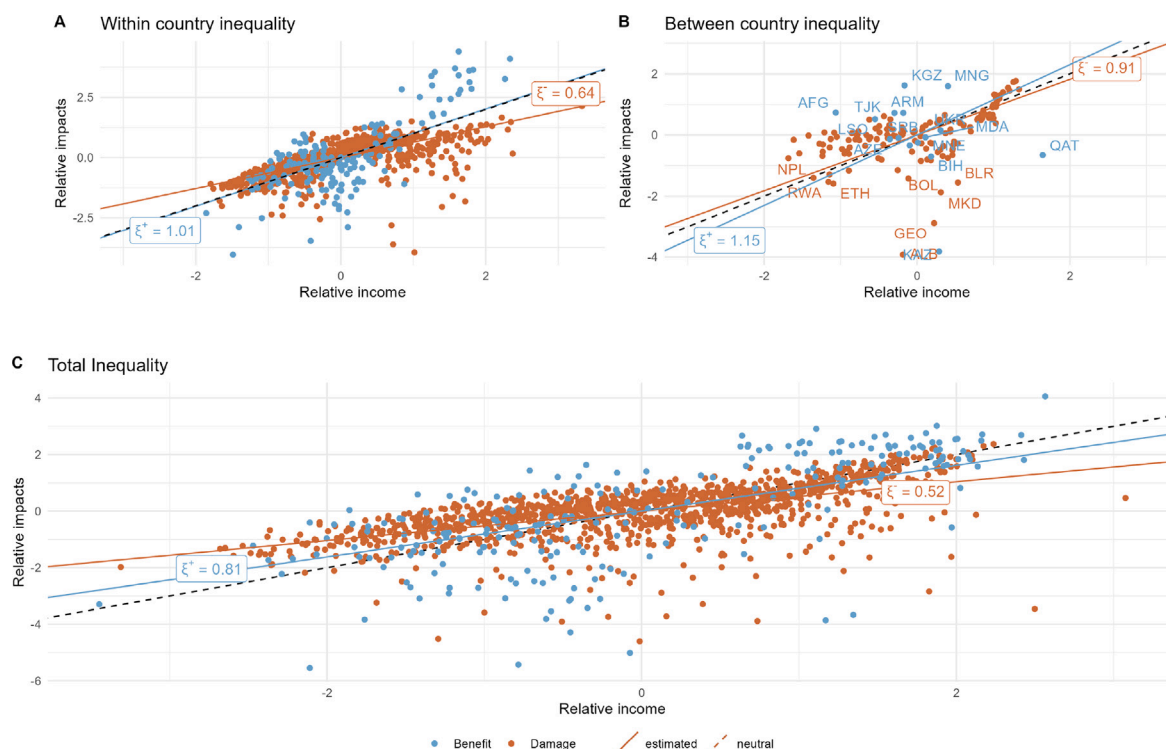
Fig. 5. Between and within-country damage incidence by 2100 under SSP3-RCP7.0. All three plots show demeaned income and impact values, panel A by country-year, panel B by year showing aggregated GDP and impact values, and panel C by year showing decile-based values. Damages (in red) and Benefits (in blue) are shown separately. Solid lines show the mean estimated relationship based on the estimated income elasticities throughout the time horizon. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

slightly progressive. All the results underline the importance of considering not only differentiated climate effects between countries, as well-established in the literature, but also within. The present paper represents a first attempt at doing this.

Several caveats and additional research directions remain, based on these results. First, in this paper, we analyzed the distributional consequences of impacts from temperature only. It does not follow that future impacts from other dimensions of the climate – such as rainfall, humidity, and extreme weather events – will necessarily have the same consequences on the distribution of income within countries. Similarly, damages that have been limited or have not occurred in the past (*e.g.*, sea level rise, ecosystem tipping points) are not factored in our analysis and may have uneven consequences along the income distribution within and between countries. Secondly, concerning inequality, dimensions other than income or consumption would be essential to identify impacts for different socioeconomic subgroups. Third, country-level data assumes a homogeneous spatial distribution of the income deciles within a country. A more spatially fine-grained analysis, for instance, at the sub-national level, would be relevant to address this simplification and to identify spatial hot spots. Finally, capturing adaptation through average income levels representing private and public adaptive capacity, is a simple proxy, and including more specific adaptive capacity indices or variables could provide a better measure of actual adaptive capacity and their effect on residual climate impacts.

CRediT authorship contribution statement

Martino Gilli: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matteo Calcaterra:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Johannes Emmerling:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Francesco Granella:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.103012.

References

Anthoff, David, Tol, Richard S.J., 2012. Schelling's conjecture on climate and development: A test. In: Hahn, Robert W., Ulph, Alistair (Eds.), Climate Change and Common Sense: Essays in Honour of Tom Schelling. Oxford University Press, Oxford, pp. 260–274.

Barreca, Alan, Clay, Karen, Deschênes, Olivier, Greenstone, Michael, Shapiro, Joseph S., 2015. Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. Amer. Econ. Rev. 105 (5), 247–251.

Burke, Marshall, Hsiang, Solomon M., Miguel, Edward, 2015. Global non-linear effect of temperature on economic production. Nature 527 (7577), 235–239.

Carleton, Tamma, Jina, Amir, Delgado, Michael, Greenstone, Michael, Houser, Trevor, Hsiang, Solomon, Hultgren, Andrew, Kopp, Robert E., McCusker, Kelly E., Nath, Ishan, et al., 2022. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. Q. J. Econ. 137 (4), 2037–2105.

Casey, Gregory, Shayegh, Soheil, Moreno-Cruz, Juan, Bunzl, Martin, Galor, Oded, Caldeira, Ken, 2019. The impact of climate change on fertility. Environ. Res. Lett. 14 (5), 054007.

Cattaneo, Cristina, Beine, Michel, Fröhlich, Christiane J., Kniveton, Dominic, Martinez-Zarzoso, Inmaculada, Mastrorillo, Marina, Millock, Katrin, Piguet, Etienne, Schraven, Benjamin, 2019. Human migration in the era of climate change. Rev. Environ. Econ. Policy 13 (2), 189–206.

Cevik, Serhan, Jalles, João Tovar, 2023. For whom the bell tolls: Climate change and income inequality. Energy Policy 174, 113475.

Cohen, François, Dechezleprêtre, Antoine, 2022. Mortality, temperature, and public health provision: evidence from Mexico. Am. Econ. J. Econ. Policy 14 (2), 161–192.

Dasgupta, Shouro, Emmerling, Johannes, Shayegh, Soheil, 2023. Inequality and growth impacts of climate change–insights from South Africa. Environ. Res. Lett. 18 (12), 124005.

De Cian, Enrica, Wing, Ian Sue, 2019. Global energy consumption in a warming climate. Environ. Resour. Econ. 72 (2), 365–410.

de Laubier Longuet Marx, Nicolas, Espagne, Etienne, Ngo Duc, Thanh, 2019. Non-linear impacts of climate change on income and inequality in vietnam. AfD Rep. 36.

Dell, Melissa, Jones, Benjamin F., Olken, Benjamin A., 2012. Temperature shocks and economic growth: Evidence from the last half century. Am. Econ. J.: Macroecon. 4 (3), 66–95.

Dennig, Francis, Budolfson, Mark B., Fleurbaey, Marc, Siebert, Asher, Socolow, Robert H., 2015. Inequality, climate impacts on the future poor, and carbon prices. Proc. Natl. Acad. Sci. 112 (52), 15827–15832.

Deryugina, Tatyana, Hsiang, Solomon M., 2014. Does the Environment Still Matter? Daily Temperature and Income in the United States. Technical Report, National Bureau of Economic Research.

Deschênes, Olivier, Greenstone, Michael, 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Amer. Econ. Rev. 97 (1), 354–385.

Desmet, Klaus, Rossi-Hansberg, Esteban, 2015. On the spatial economic impact of global warming. J. Urban Econ. 88, 16–37.

Dietz, Simon, Gollier, Christian, Kessler, Louise, 2018. The climate beta. J. Environ. Econ. Manag. 87, 258–274.

Diffenbaugh, Noah S., Burke, Marshall, 2019. Global warming has increased global economic inequality. Proc. Natl. Acad. Sci. 116 (20), 9808–9813.

Eyring, Veronika, Bony, Sandrine, Meehl, Gerald A., Senior, Catherine A., Stevens, Bjorn, Stouffer, Ronald J., Taylor, Karl E., 2016. Overview of the coupled model intercomparison project phase 6 (CMIP6) experimental design and organization. Geosci. Model Dev. 9 (5), 1937–1958.

Gazzotti, Paolo, 2022. RICE50+: DICE model at country and regional level. Soc.-Environ. Syst. Model. 4, 18038.

Graff Zivin, Joshua, Hsiang, Solomon M., Neidell, Matthew, 2018. Temperature and human capital in the short and long run. J. Assoc. Environ. Resour. Econ. 5 (1), 77–105.

Graff Zivin, Joshua, Neidell, Matthew, 2014. Temperature and the allocation of time: Implications for climate change. J. Labor Econ. 32 (1), 1–26.

Hsiang, Solomon, Oliva, Paulina, Walker, Reed, 2019. The distribution of environmental damages. Rev. Environ. Econ. Policy 13 (1), 83–103.

Isaac, Morna, Van Vuuren, Detlef P., 2009. Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. Energy Policy 37 (2), 507–521.

Jiao, Xiyu, Pretis, Felix, Schwarz, Moritz, 2023. Testing for coefficient distortion due to outliers with an application to the economic impacts of climate change. J. Econometrics 105547.

Kalkuhl, Matthias, Wenz, Leonie, 2020. The impact of climate conditions on economic production. Evidence from a global panel of regions. J. Environ. Econ. Manag. 103, 102360.

Kotz, Maximilian, Levermann, Anders, Wenz, Leonie, 2022. The effect of rainfall changes on economic production. Nature 601 (7892), 223–227, Number: 7892 Publisher: Nature Publishing Group.

Liu, Maggie, Shamdasani, Yogita, Taraz, Vis, 2023. Climate change and labor reallocation: Evidence from six decades of the Indian census. Am. Econ. J. Econ. Policy 15 (2), 395–423.

Malpede, Maurizio, Percoco, Marco, 2021. Climate Change and Income Inequalities. Technical Report, Working Paper Series.

Meinshausen, Malte, Raper, Sarah C.B., Wigley, Tom M.L., 2011. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6–Part 1: Model description and calibration. Atmospheric Chem. Phys. 11 (4), 1417–1456.

Mendelsohn, Robert, Dinar, Ariel, Williams, Larry, 2006. The distributional impact of climate change on rich and poor countries. Environ. Dev. Econ. 159–178.

Mendelsohn, Robert, Emanuel, Kerry, Chonabayashi, Shun, Bakkensen, Laura, 2012. The impact of climate change on global tropical cyclone damage. Nature Clim. Change 2 (3), 205–209, Number: 3 Publisher: Nature Publishing Group.

Narayan, Kanishka B., O'Neill, Brian C., Waldhoff, Stephanie, Tebaldi, Claudia, 2023a. A consistent dataset for the net income distribution for 190 countries, aggregated to 32 geographical regions and the world from 1958–2015. Earth Syst. Sci. Data Discuss. 1–23, Publisher: Copernicus GmbH.

Narayan, Kanishka B., O'Neill, Brian C., Waldhoff, Stephanie T., Tebaldi, Claudia, 2023b. Non-parametric projections of national income distribution consistent with the Shared Socioeconomic Pathways. Environ. Res. Lett. 18 (4), 044013.

Newell, Richard G., Prest, Brian C., Sexton, Steven E., 2018. The GDP-temperature relationship: Implications for climate change damages. p. 63, RFF Working Paper Series.

Newell, Richard G., Prest, Brian C., Sexton, Steven E., 2021. The GDP-temperature relationship: implications for climate change damages. J. Environ. Econ. Manag. 108, 102445.

Nordhaus, William D., 2017. Revisiting the social cost of carbon. Proc. Natl. Acad. Sci. 114 (7), 1518–1523.

O'Neill, Brian C., Kriegler, Elmar, Ebi, Kristie L., Kemp-Benedict, Eric, Riahi, Keywan, Rothman, Dale S., van Ruijven, Bas J., van Vuuren, Detlef P., Birkmann, Joern, Kok, Kasper, Levy, Marc, Solecki, William, 2017. The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. Global Environ. Change 42, 169–180.

Paglialunga, Elena, Coveri, Andrea, Zanfei, Antonello, 2022. Climate change and within-country inequality: New evidence from a global perspective. World Dev. 159, 106030.

Palagi, Elisa, Coronese, Matteo, Lamperti, Francesco, Roventini, Andrea, 2022. Climate change and the nonlinear impact of precipitation anomalies on income inequality. Proc. Natl. Acad. Sci. 119 (43), e2203595119.

Pretis, Felix, Schwarz, Moritz, Tang, Kevin, Haustein, Karsten, Allen, Myles R., 2018. Uncertain impacts on economic growth when stabilizing global temperatures at 1.5 C or 2 C warming. Phil. Trans. R. Soc. A 376 (2119), 20160460.

Riahi, Keywan, Van Vuuren, Detlef P., Kriegler, Elmar, Edmonds, Jae, O'neill, Brian C., Fujimori, Shinichiro, Bauer, Nico, Calvin, Katherine, Dellink, Rob, Fricko, Oliver, et al., 2017. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Chang. 42, 153–168.

Santos, Carlos, Hendry, David F., Johansen, Soren, 2008. Automatic selection of indicators in a fully saturated regression. Comput. Statist. 23, 317–335.

Sedova, Barbora, Kalkuhl, Matthias, Mendelsohn, Robert, 2019. Distributional impacts of weather and climate in rural India. Econ. Disasters Clim. Chang..

Sherwood, S.C., Webb, M.J., Annan, J.D., Armour, K.C., Forster, P.M., Hargreaves, J.C., Hegerl, G., Klein, S.A., Marvel, K.D., Rohling, E.J., Watanabe, M., Andrews, T., Braconnot, P., Bretherton, C.S., Foster, G.L., Hausfather, Z., von der Heydt, A.S., Knutti, R., Mauritsen, T., Norris, J.R., Proistosescu, C., Rugenstein, M., Schmidt, G.A., Tokarska, K.B., Zelinka, M.D., 2020. An assessment of Earth's climate sensitivity using multiple lines of evidence. Rev. Geophys. 58 (4), e2019RG000678.

Somanathan, Eswaran, Somanathan, Rohini, Sudarshan, Anant, Tewari, Meenu, 2021. The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. J. Polit. Econ. 129 (6), 1797–1827.

Taconet, Nicolas, Méjean, Aurélie, Guivarch, Céline, 2020. Influence of climate change impacts and mitigation costs on inequality between countries. Clim. Change 160 (1), 15–34.

Tol, Richard S.J., 2021. The distributional impact of climate change. Ann. New York Acad. Sci. 1504 (1), 63–75, _eprint: https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/nyas.14497.