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 the richest suffer the lowest damages. In a Reference scenario without additional climate action (3.1°C warming), we estimate that climate impacts could lead to an increase of the Gini index by up to six points, notably in Sub-Saharan Africa. Globally, we estimate that around three-quarters of the total variation in climate impacts is due to between-country heterogeneity, and one-quarter is due to within-country inequality. We project damages to 2100 through the RICE50+ model and estimate the income elasticity of damages within countries. Our estimates indicate that the total economic impact of climate change is regressive, with an income elasticity of damages of 0.72 under our preferred specification. We find climate impacts to be especially regressive in poorer and hotter countries. While global damages are sensitive to the functional form of the damage function, the estimated income elasticity parameter is robust across different specifications.

Keywords: Climate change, climate damages, climate impacts, inequality, panel regression, vulnerability

JEL codes: O11 O44 Q54 Q56

1 Introduction

It is by now a scientific consensus that climate change has and will significantly impact 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).

Climate change is expected to have heterogeneous impacts in space and among households with different income levels, occupations, and consumption patterns, among other characteristics. Such heterogeneity will also affect the degree of inequality both within and between countries. Specifically, climate change may exacerbate between-country 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, the effects of climate change are also expected to differ across households. For example, small-scale farmers in developing countries have limited means to adapt to climate change (see, e.g., Cohen and Dechezleprêtre (2022) for the higher vulnerability of poorer households to mortality impacts), making them more vulnerable to droughts, floods, and other disasters exacerbated by global warming. This vulnerability can lead to food insecurity, poverty, displacement, and widening the economic gap between rich and poor. 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 extent to which the impact of temperature change on inequality holds within different countries remains unclear. Higher vulnerability to climate change in developing countries translates to greater inequality, while the impact on income distribution in developed countries is less pronounced (Cevik and Jalles, 2023). Indeed, climate change could increase inequality between and within communities (Hsiang et al., 2019). Preliminary evidence 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., 2020; Paglialunga et al., 2022).

This study aims at contributing to the existing literature by analyzing the impact of climate change on income inequality within countries in a novel way. 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 through 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]

We show that, although the choice of damage function strongly influences global projected impacts, the distributional consequences of climate impacts are consistently projected to be regressive within countries, across all three damage function specifications. 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. We find that the vulnerability to rising temperatures decreases almost monotonically across income deciles within countries. Moreover, in line with the existing literature, we find that most climate damages will be concentrated in the hotter and poorer regions of the world so that those most affected by climate change will be the poorest *between* and *within countries*. Under our preferred econometric specification for the damage function, the within-country variation of climate damages accounts for almost 24% of the variance of total damages by 2100, with the remaining 76% explained by variation in damages across countries.

In addition, we estimate the global income elasticity of damages, which has significant implications for the Social Cost of Carbon (Dennig et al., 2015). This value is estimated between 0.69 and 0.84 for the three impact functions, is stable over time, but also shows significant heterogeneity across countries. In particular, we find that the elasticity is lower in richer and colder countries, implying a more regressive distribution of projected climate impacts in those countries.

We first present the empirical strategy to estimate the impact functions by income decile. After describing the data in Section 3, we present the results in Section 4. The following sections discuss the projected damages until 2100 (Section 5) and the income elasticity of

[1] We estimate the impact functions of Burke et al. (2015), Kalkuhl and Wenz (2020), and Jiao et al. (2021), as detailed below.

climate damages (Section 6), followed by the conclusions in Section 7.

2 Empirical strategy

We estimate 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. (2021), respectively. We estimate them separately for each decile $q = 1, ..., 10$ of the (within-country) net income distribution. We model the growth in the income of each decile as a function of annual mean temperature, annual cumulative 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 usual 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:

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

with i and t indexing country and year, respectively. y_{it} is the real per capita income of decile q in logarithm. We define decile income as the decile share multiplied by real per capita GDP. 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, $\zeta_i t$

[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.

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:

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

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. (2021). By observing damages from temperature shocks, we can infer that adaptation to climate shocks is costly. It follows that higher income relaxes the budget constraint under which economic agents undertake the optimal adaptation decision. Hence, the richer 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.

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

[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

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 that are less exposed to the negative impacts on the productivity of higher temperatures (see *e.g.* Somanathan et al. (2021)) or with investment 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 [4]. Jiao et al. (2021) 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 summarise, we estimate a separate set of coefficients for each income decile. We evaluate how the 10 deciles of the distribution 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 for the 10 deciles. Income inequality will worsen as a result of 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 4 and 5, we focus especially on the findings from the estimation of Equation 3. In Section 6 we show

[4]We show in Section A.1 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.

that our main findings on the distribution of climate impacts within countries hold across all three impact function specifications from the literature.

3 Data

Table 1 presents the summary statistics of the variables we use for our empirical specifications. For estimating the GDP-level damage functions, we use country-level annual data on GDP per capita in constant US-$[2015] from the World Bank's Development Indicators and population-weighted annual weather data on average temperature and precipitation from the Climate Research Unit at the University of East Anglia. We aggregate monthly average temperature and precipitation at the 0.5° grid-cell level with weights coming from the population density 0.5° grid-cell level data 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.

For the inequality data based on deciles, given the strongly unbalanced nature of the panel dataset on income deciles of the well-known WIID data, we relied on a recently released dataset by Narayan et al. (2023a), who created a full dataset suitable for panel data analysis. 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. In short, they impute the missing values for income deciles with the predicted values coming from (1) consumption data when available (predicted through OLS), and (2) Gini data through Principal Component Analysis. Finally, we compute the level of average income by decile combining each decile's share with the average GDP per capita. The analysis is performed on unbalanced data (because of missing Gini or GDP data) from 1960 at the earliest to 2015 at the latest.

For the projection of climate impacts, we compare projected per-capita GDP under combined Shared Socioeconomic Pathways (SSPs) for socioeconomic variables (Population and GDP Riahi et al. (2017)) and Representative Concentration Pathways (RCPs) for country-

	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

Table 1: Summary statistics

level climate variables. In particular, we use as a reference the combined SSP3 and RCP 7.0 scenario ("SSP3-7.0"), which in CMIP6 has often been referred to as a scenario compatible with a range of business-as-usual trajectories without additional climate policy strengthening. We compare this scenario without climate impacts to the same projected per-capita GDP after we apply the impacts of temperature increases. The impacts are based on the estimated coefficients from the damage functions. Since the regression coefficients are imprecisely estimated and future projections for precipitation are not reliable, we focus our analysis on the effects of temperature, consistently 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), in simulation mode. 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 and temperatures increasing according to the high-emission RCP 7.0 scenario. The global average increase in surface temperature is around 3.1 °C by 2100 under this scenario relative to the average in the period from 1995 to 2015, according to the MAGICC climate model.

4 Empirical results

Estimates from Equation 3 confirm that national income plays a crucial role in reducing vulnerability to deviations from the typical temperature. The estimated coefficients are presented in Table 2. Notably, two key factors contribute to larger damages in lower-income countries.

Firstly, their damage function exhibits a steeper curve. This implies that as temperatures deviate from the optimal level in a warming world, marginal damages grow faster in poorer countries. 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 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, Figure 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). For clarity, we fix these three income levels for visualization purposes, presenting how the damage function evolves as a third variable (GDP per capita) changes. Confidence intervals are excluded in the figure for visual clarity, and they are reported in Figure A.1 in the Appendix.

Secondly, current temperatures are already farther above the optimal temperature in poorer countries than they are in richer countries. 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 such that, assuming quadratic damage functions, a marginal increase in temperatures leads to larger losses in output growth.

Hence, as evidenced by the sign and significance of the interaction terms in Table 2, higher real per capita GDP reduces the sensitivity of income growth to changes in temperature for all deciles, across countries. This implies that households in richer countries are less vulnerable to climate shocks *ceteris paribus*, including the current climate.

Looking within countries, the damage functions of Figure 1 implied by the coefficients of

Table 2, show that the income of poorer households is more responsive to changes in temperature than the relatively richer households. In particular, they tend to see stronger reductions in income when experiencing temperature shocks in those countries that are characterized by relatively hot climates. In addition to this, we also see that the responsiveness to temperature appears to decrease almost monotonically across income deciles, so that a household in a given decile will tend to see lower damages (or benefits) from rising temperature than a household in the preceding decile. Moreover, this pattern holds across different country-level income levels (per capita GDP).

The pattern by which the poorer deciles tend to suffer larger damages from rising temperatures than the richer deciles *within the same countries*, together with the temperature projections, is the key result underpinning our findings on the distributional consequences of climate change impacts in Sections 5 and 6.

To summarise, climate damages are greater for poorer individuals in both low- and high-income countries. In particular, the first (poorest) decile tends to be significantly more vulnerable than the rest of society. As projections of damages in Section 5 make it more clear, income moderates damages within countries, and climate change is projected to increase inequalities both within and between countries (Diffenbaugh and Burke, 2019).

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***	0.1326***
	(0.0621)	(0.0399)	(0.0352)	(0.0317)	(0.0287)	(0.0268)	(0.0252)	(0.0238)	(0.0227)	(0.0237)	(0.0234)
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)	(0.0007)
Temperature X GDP($t-1$)	-0.0152**	-0.0124***	-0.0126***	-0.0124***	-0.0122***	-0.0120***	-0.0120***	-0.0122***	-0.0121***	-0.0107***	-0.0125***
	(0.0063)	(0.0040)	(0.0036)	(0.0032)	(0.0030)	(0.0028)	(0.0026)	(0.0025)	(0.0024)	(0.0026)	(0.0025)
Temperature Sq. X 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})	(8.65×10^{-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	5,636
R^2	0.09430	0.09704	0.10928	0.13340	0.16973	0.20311	0.24298	0.27602	0.27332	0.14926	0.30489
Within R^2	0.06357	0.02177	0.02327	0.03068	0.03692	0.04902	0.06888	0.08896	0.08365	0.04845	0.11486

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.

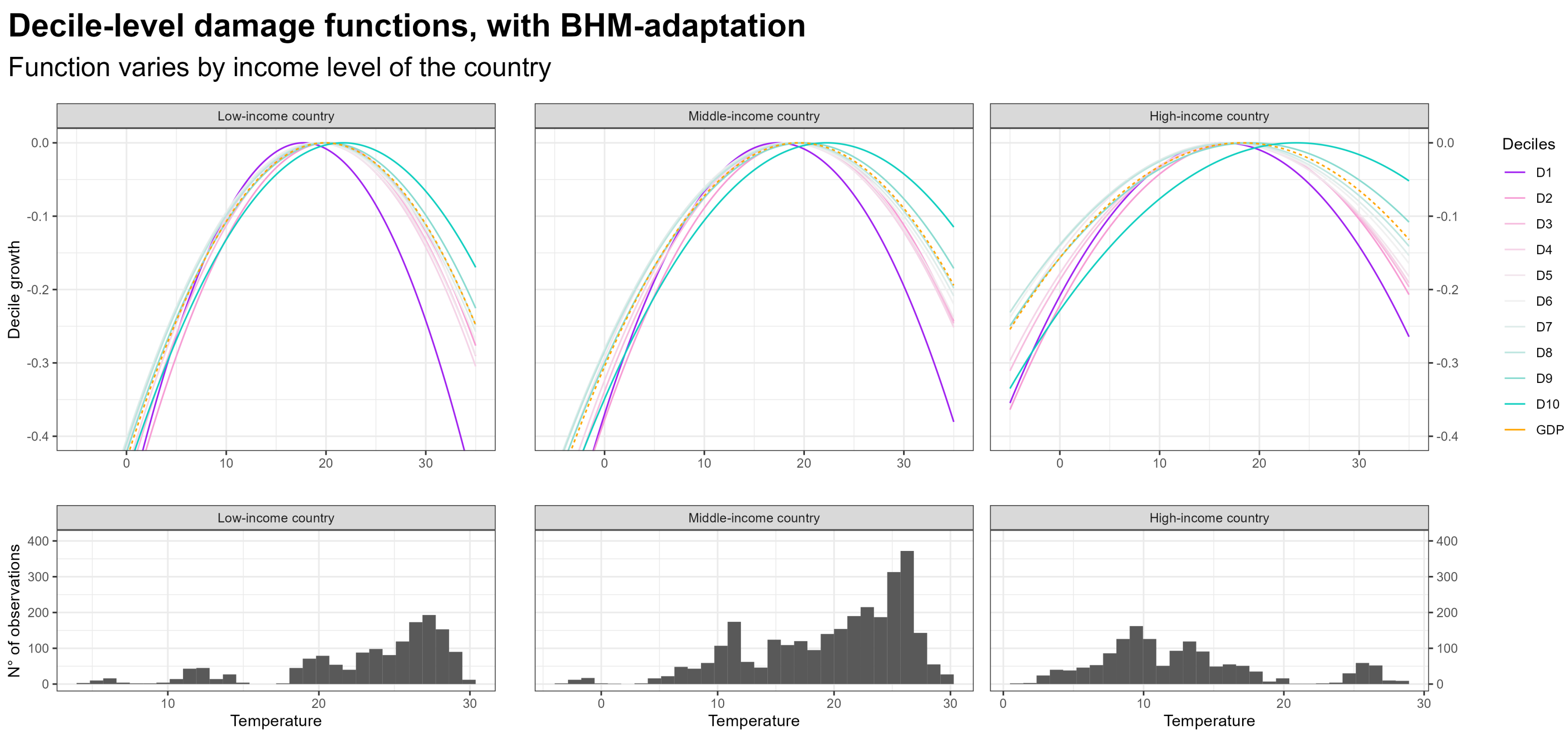

Figure 1: Damage functions at the decile level. *D1* to *D10* indicate deciles from the poorest to the richest. *GDP* indicates the country-level damage functions. Decile-level damage functions with income-driven adaptation for three selected countries at different levels of income. The shape of the 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.1 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.

5 Projected distributional impacts

We next explore the distributional impacts of climate damages and the mitigating potential of income through the end of the century using the projected trajectories of temperature, population, and GDP of the RICE50+ model, described in detail in Gazzotti (2022). The model is an extension of Nordhaus's seminal DICE model (Nordhaus, 2017) and features by default 57, but up to 160 countries or regions. Temperature is downscaled to the regional level based on the CMIP6 model ensemble. From the model, we extract projections for total GDP and population at the regional level, combining them with projections on decile-level income for different SSP scenarios available from Narayan et al. (2023b).

To create our baseline scenario with no climate impacts, we let income of decile q in year t and country i evolve according to:

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

where g is the counterfactual growth rate under no climate impacts from the SSPs. The evolution of decile-level average income with climate impacts is

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

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. Damages and benefits are set to increase with projected climate change as average country temperature increases. Under the BHM specification, δ_{it}^{q} is:

$$\delta_{it}^{q,BHM} = \widehat{\beta}_1^{\,q}(Temp_{it} - Temp_{i0}) + \widehat{\beta}_2^{\,q}(Temp_{it}^2 - Temp_{i0}^2)$$

Under the KW specification, it is:

$$\delta_{it}^{q,KW} = \widehat{\beta}_0^{\,q}\Delta Temp_{it} + \widehat{\beta}_1^{\,q}\Delta Temp_{it-1} + \widehat{\beta}_2^{\,q}\Delta Temp_{it} * Temp_{it-1} + \widehat{\beta}_3^{\,q}\Delta Temp_{it-1} * Temp_{it-1}$$

Under the BHM-Adaptation specification, it is:

$$\delta_{it}^{q,BHM-Adaptation} = (Temp_{it} - Temp_{i0})(\widehat{\beta}_1^{q} + \widehat{\beta}_3^{q}y_{it-1}) + (Temp_{it}^2 - Temp_{i0}^2)(\widehat{\beta}_2^{q} + \widehat{\beta}_4^{q}y_{it-1})$$

where $Temp_{i0}$ is the 2015 level of temperature in the region i and y_{it-1} is the lagged region-level per capita GDP 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 as a consequence.

Damages for each decile q in time t are then defined as the difference in per-capita income levels between the projected y_{it}^{q} under climate change and counterfactual $\widetilde{y_{it}}^{q}$ without climate impacts, relative to the counterfactual[5] :

$$D_{it}^{q} = \frac{\widetilde{Y_{it}^{q}} - Y_{it}^{q}}{\widetilde{Y_{it}^{q}}}$$

We report our estimated global damages over time for all damage function specifications, as implied by our empirical results, in Figure A.2 in Section A.2, where we also explain some discrepancies with previous results on global projected damages. In short, by 2100, under a 3.1°C warming scenario relative to the 1995-2015 average, global damages to per capita GDP are projected to be 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)[6]. In the rest of the paper, we focus on how those damages are projected to be distributed within countries, displaying the results under our preferred specification. At the same time, one of our main findings is that the conclusion that damages are projected to be regressive within countries is robust to the choice of the damage function specification.

Moving from the global level to the decile-country level as represented in the RICE50+ model, in Figure 2, we display the overall incidence of projected climate damages from temperatures across income deciles, for all countries. For each decile group, we include that decile for all countries in our sample. Projected damages decrease with income within countries, with median impacts for D9 below 10% of per capita income and impacts for D10 centered just below 0. Projected damages under the BHM-adaptation specification are instead close, on average, across the other deciles, which correspond to the relatively poorer households. Moreover, the range and variance of projected damages across countries is larger for the lowest deciles, D1 and D2, than for the other deciles. Figures A.4 and A.5 in Section A.3 of the Appendix show that damages are projected to be regressive within countries for all three considered damage functions.

Given the well-know regional heterogeneity in projected climate damages, as they depend on current climates that vary across latitudes, in Figure 3 we display how the projected regressive damages vary across countries. In panel (a), we plot the difference in percentage points between projected damages for the poorest within each country (D1) and the richest

[5] Analogously, country-level damages are defined as $D_{it} = \frac{\widetilde{Y_{it}} - Y_{it}}{\widetilde{Y_{it}}}$.

[6] In Figure A.8 in Section A.5, we display projected damages across four SSP-RCP scenarios for all three damage functions.

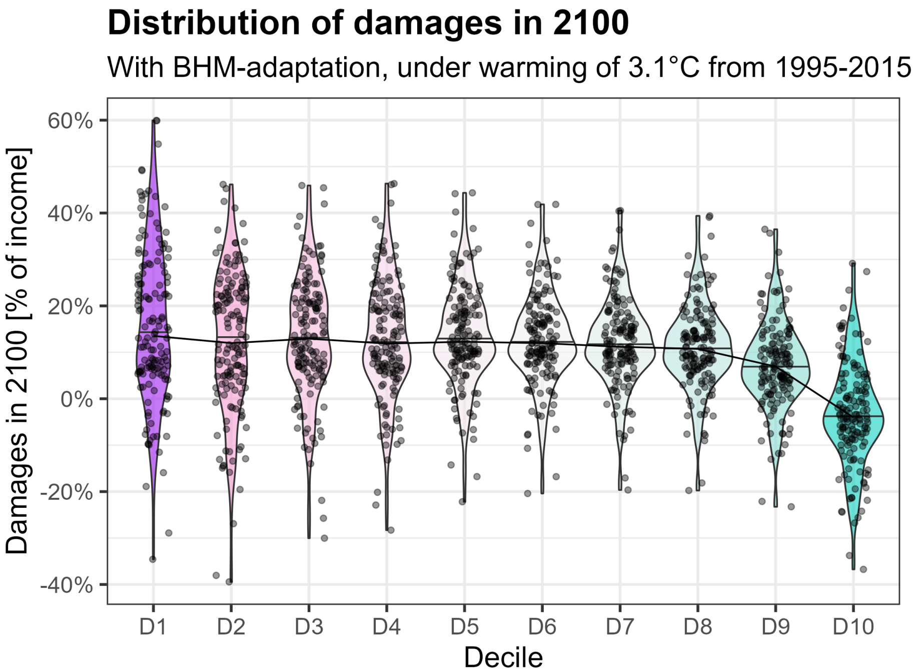

Figure 2: Projected decile-level impacts in 2100 under SSP3-7.0 scenario. Each dot represents the projected impact on decile-level income for a given income decile in one of the 154 countries of RICE50+. Dot placement is slightly perturbed for visualization purposes. The solid black line connects the median of the distribution, for each decile, of projected impacts across regions.

(D10), so that a higher value implies that the relatively poor in that country are more exposed to damages from rising temperatures and viceversa[7]. Figure 3a shows that the more strongly regressive consequences for the distribution of incomes within countries will come in the currently hotter and poorer parts of the world, as implied by Figure 1. The relatively poor within countries are particularly more exposed than the relatively rich in Sub-Saharan Africa, the Middle East, and South Asia, as well as parts of Central and South America, but this is true for basically every country in our sample, Mongolia being the lone exception.

Figure 3b displays the consequences for the Gini index by country of our projected decile-level climate impacts under the SSP3-RCP7.0 scenario, implying warming of +3°C by 2100[8]. Consistently with the findings displayed in the upper panel, higher 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 in 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 (2022), despite the different econometric models used.

The importance of accounting for the heterogeneous impacts of climate damages within countries can be further underlined by decomposing the variance of the projected damages at the decile-country level in 2100, which are displayed in the upper panel of Figure 4.

Following the definition of the variance of a variable Y,

$$Var(Y) = \underbrace{VarE[Y|X]}_{\textit{Between component}} + \underbrace{E[Var(Y|X)]}_{\textit{Within component}}$$

we find that the within-country (so across income deciles) variance of projected damages in 2100 accounts for approximately 24% of the total variance, with the rest coming from between-country variance in projected damages.

Figure 4 clarifies this further. The upper panel plots the projected-damages for all decile-country observations in 2100 (so ten observations per country) against the projected damages to per capita income, as defined above, by decile-country. The negative slope is implied

[7]in Figure A.3 in Section A.3 we display projected damages in 2100 to per capita income for all deciles in all countries, for completeness

[8]Figure A.9 in Section A.5 displays the projected increase in global Gini across four SSP-RCP scenarios. To compute the global Gini for that figure, we first compute the projected change in country-level Gini under a warming scenario relative to the counterfactual and then compute a weighted average by population across countries.

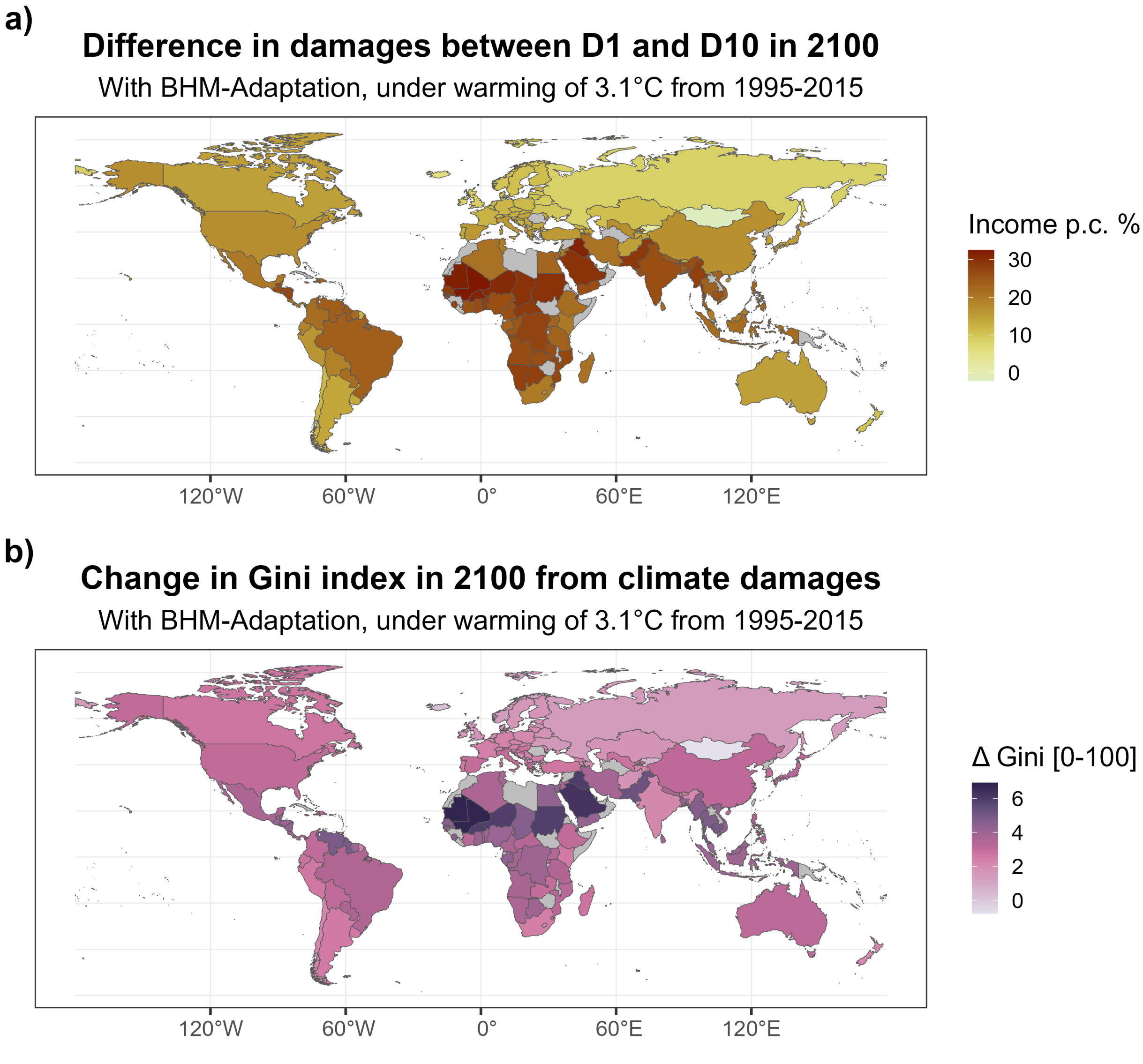

Figure 3: Differences in damages between D1 and D10 (top) and impact of climate change on the Gini index (bottom) by 2100 under SSP3-RCP7.0.

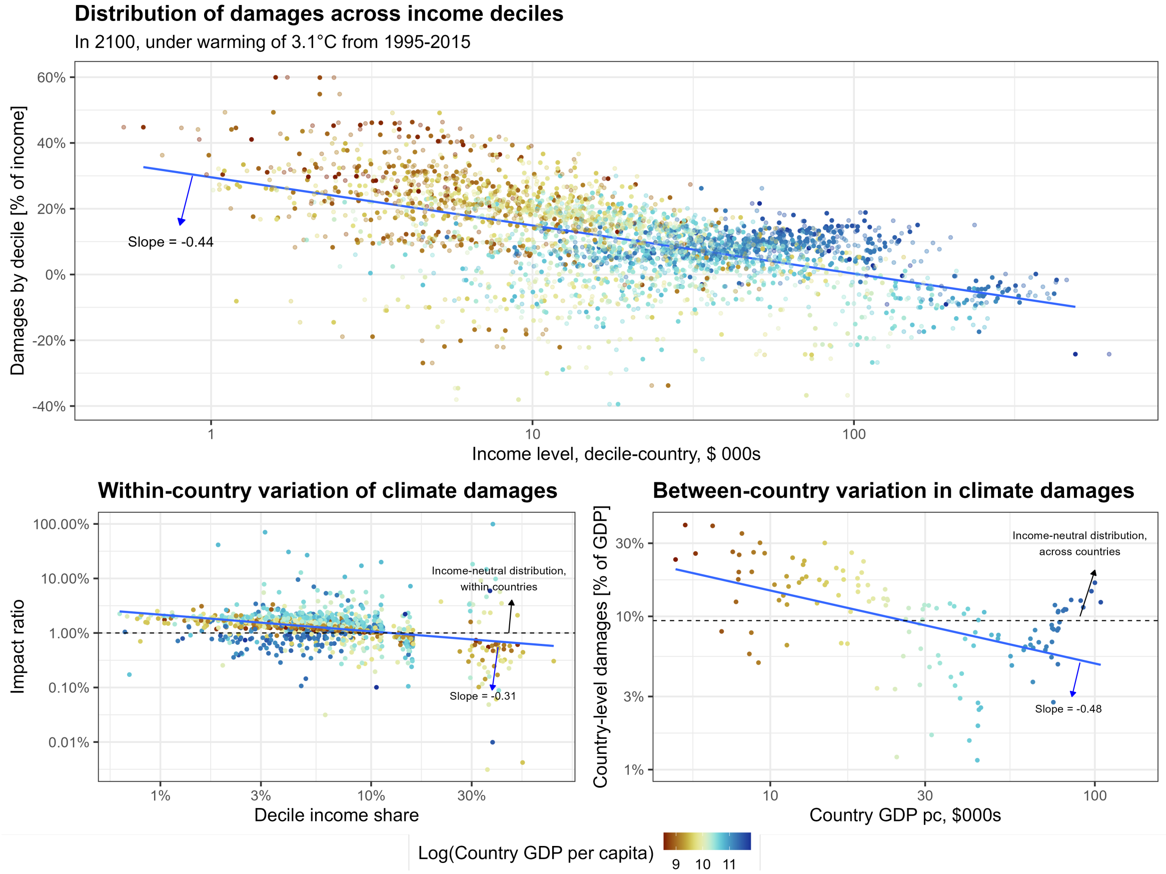

Figure 4: Between and within-country damage incidence by 2100 under SSP3-RCP7.0.

by the overall regressivity of projected damages at the global damages, so that the world's poorest households suffer the largest projected damages and viceversa. This regressivity is composed of two parts: the *between-country* component and the *within-country* component. The between-country component comes from the fact that today's poorest countries are also those that are projected to suffer the most negative consequences from climate change (which has already been shown in several studies, including Burke et al. (2015) and Kalkuhl and Wenz (2020) since poor countries tend also to be in hot climates). The bottom-right panel of Figure 4 displays this relation under our preferred econometric specification of the damage function. The within-country component is specific to the incidence of climate damages within countries and is the contribution of this paper. The bottom-left panel of Figure 4 displays this relation, which captures the income elasticity of damages within countries. In the next section we delve further into the estimation of this elasticity.

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 income distribution within countries - has important implications for the socially optimal climate policy, for poverty and political economy considerations, and ultimately for the Social Cost of Carbon (Dennig et al., 2015). Following the notation of Dennig et al. (2015), the damage share of the qth decile in country i depends on its income share within the country (or in their case, region), and on an impact elasticity parameter ξ:[9]

$$\frac{D_{it}^{q}}{D_{it}} = a_i\left(\frac{Y_{it}^{q}}{Y_{it}}\right)^{\xi}. \tag{4}$$

Damages are proportional to income (*i.e.* distribution-neutral) when $\xi = 1$, and fall disproportionately on the poor when $\xi < 1$ and on the rich when $\xi > 1$. Taking logs and substituting $ln(a_i) = \alpha_i$, we obtain a log-linear equation with which we can recover ξ through a standard OLS regression:

$$ln\left(\frac{D_{it}^{q}}{D_{it}}\right) = \alpha_i + \xi ln\left(\frac{Y_{it}^{q}}{Y_{it}}\right) + \epsilon_{qi} \tag{5}$$

where ϵ_{qi} is a random error term.[10] Using the projected damages at the decile level over time and across countries, we can thus estimate the income elasticity based on our estimated impact function. That is, we use $\frac{D_{it}^{q}}{D_{it}}$ and $\frac{Y_{it}^{q}}{Y_{it}}$ from the projections calculated in Section 5 and estimate ξ.

Since $\frac{D_{it}^{q}}{D_{it}}$ may be negative for some decile-country-year observations, i.e., they see income benefits from rising temperatures- because their climates start from a temperature to the left of their estimated optimal temperature (so that they are on the upward-sloping part of the curve) we take the absolute value of the projected decile impacts. In Section A.4, we show that our estimates of the income elasticity of climate impacts are robust to excluding those observations with negative damages (climate benefits), and to the choice of fixed effects.

We estimate the Equation 5 and present the income elasticity of impacts for different functional forms of the damage function in Table 3. While global projected damages are

[9]Here, a_i represents a scaling factor per country, which is computed such that the damage shares add up to one across deciles, as in Dennig et al. (2015).

[10]Notice that if we multiplied the fraction $\frac{D_{it}^{q}}{D_{it}}$ on the left-hand side of (5) by $\frac{Y_{it}^{q}}{Y_{it}^{q}}\frac{Y_{it}}{Y_{it}}$, we could recover an estimate of $\xi - 1$. This would imply that an income-neutral distribution of climate impacts is characterized by a horizontal line of slope 0, which is what we do in figure 4 for visualization purposes.

sensitive to the choice of the function as shown in Newell et al. (2021) and in Figure A.2, the income elasticity of damages is not as sensitive. In particular, projected climate damages are shown to be regressive across all three considered impact function specifications. This income elasticity parameter is estimated at 0.84 under BHM, 0.72 under the BHM-Adaptation specification, and 0.69 under the KW specification. All three estimates of the elasticity are furthermore significantly different from 1 (with $p < 0.001$). This implies that projected climate impacts can be summarized as being overall regressive within countries, with the poorer parts of the country suffering a relatively higher burden of those impacts, regardless of the choice of the damage function.

Table 3: Estimates of the income elasticity of climate damages.

Dependent Variables:	Relative impacts - BHM	Relative impacts - BHM adapt.	Relative impacts - KW
Model:	(1)	(2)	(3)
Variables			
Relative income	0.8417***	0.7186***	0.6927***
	(0.0052)	(0.0018)	(0.0042)
Fixed-effects			
Time	Yes	Yes	Yes
Country	Yes	Yes	Yes
Fit statistics			
Country	23,680	23,680	23,680
R^2	0.58666	0.39805	0.47163
Within R^2	0.53661	0.31805	0.36948

Clustered (Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The dependent variable is the share of damages of a decile with respect to its country's total damages, calculated in the previous section.
The independent variable is the share of income of a decile with respect to its country's total income.
The unit of analysis is country-decile. Regressions include year-fixed effects and country-fixed effects.

We then explored potential heterogeneity across countries in the estimated income elasticity of damages. We did so by estimating a separate ξ parameter with observations from that country only. Focusing on the BHM-Adaptation specification, Figure A.7 in Section A.4 shows the distribution of the country-specific income elasticity of impacts. In order to study what characteristics of countries can explain the variation of the estimated income elasticity

Table 4: Estimates of the income elasticity of climate damages, under the BHM-Adaptation specification, by sub-samples.

	Above med. GDP	Below med. GDP	Above med. temperature	Below med. temperature
Dependent Variable:	Relative impacts			
Model:	(1)	(2)	(3)	(4)
Variables				
Relative income	0.8116***	0.6275***	0.4310***	1.100***
	(0.0616)	(0.0430)	(0.0349)	(0.0447)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Fit statistics				
Country	12,160	11,520	11,840	11,840
R^2	0.39045	0.42688	0.51771	0.44234
Within R^2	0.30594	0.35731	0.41152	0.38161

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

parameter in the cross-section, we divided the countries in RICE50+ into two sub-samples, by per capita GDP and by annual mean temperature. As shown in 4 and as it follows from our empirical results in section 4, we found that damages are more regressive in poorer countries (those with a below-median per capita GDP, $\xi = 0.63$) as well as in hotter countries (those with below median annual temperature, $\xi = 0.43$).

Finally, we study whether and how the ξ parameter varies over time in selected countries. We can estimate a separate ξ for each country-year combination with 10 observations, given by the relative income and projected impacts for those deciles in that country-year. Figure A.6 in Section A.4 shows that the income-elasticity (the blue line of best fit across observations within each cell) is very stable over time for all considered countries.

7 Conclusion

We study empirically how changing temperatures have had differentiated economic impacts on households, here disaggregated by income deciles within countries. We have shown that projected climate impacts from rising temperatures will fall more heavily on the poorest within countries and that this finding is robust to the choice of the impact function. We use our estimates of projected economic impacts by income decile and region to obtain an empirical estimate of the income elasticity of the damage parameter. While there is significant regional heterogeneity, our central estimate implies regressive damages with an income elasticity of 0.72, while impacts can also be slightly progressive, at an average value of 1.1 (in relatively cold countries) up to being very regressive at 0.43 (in relatively hot countries). These results also indicate the importance of between-country inequality and heterogeneity, which we estimate to make up around three-quarters of the total inequality effect of climate change.

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, with regard to inequality, dimensions other than income or consumption would be important to identify impacts for different socioeconomic subgroups. Third, country-level data assumes 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.

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A Appendix

A.1 Damage functions - robustness checks

Table A.1: Damage functions, BHM with adaptation

	Base		Linear trends		Quadratic trends
Dependent Variable:			GDP pc growth		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Temperature	0.1085***	0.1167***	0.1032***	0.1118**	0.1515***
	(0.0201)	(0.0147)	(0.0202)	(0.0532)	(0.0214)
Temperature, Squared	-0.0027***	-0.0030***	-0.0028***	-0.0028**	-0.0034***
	(0.0006)	(0.0005)	(0.0006)	(0.0011)	(0.0007)
Temperature X GDP, $t-1$	-0.0099***				-0.0145***
	(0.0021)				(0.0023)
Temperature Sq. X GDP, $t-1$	0.0002***				0.0003***
	(7.27×10^{-5})				(8.46×10^{-5})
Temperature × 5-year avg. GDP		-0.0111***			
		(0.0013)			
Temperature, Squared × 5-year avg. GDP		0.0003***			
		(4.89×10^{-5})			
Temperature × 10-year avg. GDP			-0.0097***		
			(0.0019)		
Temperature, Squared × 10-year avg. GDP			0.0003***		
			(6.85×10^{-5})		
Temperature × avg. GDP				-0.0103**	
				(0.0051)	
Temperature, Squared × avg. GDP				0.0003**	
				(0.0001)	
Fixed-effects					
Country	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Varying Slopes					
Year (Country)	Yes	Yes	Yes	Yes	Yes
Year^2 (Country)		Yes			Yes
Fit statistics					
Observations	7,064	6,743	5,989	7,064	7,064
R^2	0.30148	0.32707	0.29681	0.25665	0.37668
Within R^2	0.10810	0.06979	0.07516	0.05087	0.13087

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.2: Damage functions BHM-adaptation eliminating bottom and top 1% percentile outlier observations of decile income growth

Dependent Variable:	Decile income growth									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Temperature	0.1088**	0.1005***	0.0932***	0.0805***	0.0776***	0.0735***	0.0759***	0.0807***	0.0811***	0.1050***
	(0.0533)	(0.0333)	(0.0290)	(0.0238)	(0.0193)	(0.0167)	(0.0163)	(0.0159)	(0.0158)	(0.0231)
Temperature, Squared	-0.0026	-0.0022*	-0.0022**	-0.0019**	-0.0019***	-0.0018***	-0.0019***	-0.0020***	-0.0020***	-0.0027***
	(0.0020)	(0.0012)	(0.0010)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0008)
Temperature X GDP, $t-1$	-0.0099*	-0.0095***	-0.0089***	-0.0077***	-0.0076***	-0.0074***	-0.0077***	-0.0081***	-0.0080***	-0.0100***
	(0.0059)	(0.0035)	(0.0031)	(0.0025)	(0.0020)	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0025)
Temperature Sq. X GDP, $t-1$	0.0002	0.0002	0.0002	0.0002	0.0002**	0.0002**	0.0002***	0.0002***	0.0002***	0.0003***
	(0.0002)	(0.0001)	(0.0001)	(9.8×10^{-5})	(7.84×10^{-5})	(6.71×10^{-5})	(6.52×10^{-5})	(6.53×10^{-5})	(6.7×10^{-5})	(9.49×10^{-5})
Fixed-effects										
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Varying Slopes										
Year (Country)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	5,492	5,491	5,493	5,494	5,494	5,495	5,497	5,497	5,496	5,495
R^2	0.19209	0.13441	0.14547	0.16289	0.18783	0.20701	0.24490	0.28824	0.29056	0.17303
Within R^2	0.10095	0.02482	0.02667	0.03197	0.03037	0.03366	0.04600	0.06353	0.05907	0.03531

Clustered (Country) standard-errors in parentheses

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

Note: eliminating bottom and top 1% percentile outlier observations of decile income growth.

Table A.3: Damage functions with IIS estimator

	D1	D2	D3	D4	D5
Temperature	0.11175 (1.52638)	0.06821 (1.61143)	0.04932 (1.32773)	0.03276 (1.00403)	0.02294 (0.79351)
Temperature, Squared	-0.00180 (-0.86531)	-0.00109 (-0.91190)	-0.00092 (-0.88284)	-0.00057 (-0.61652)	-0.00040 (-0.49056)
Temperature X GDP(t-1)	-0.01092 (-1.38372)	-0.00672 (-1.47414)	-0.00481 (-1.20310)	-0.00292 (-0.83278)	-0.00180 (-0.57902)
Temperature Sq. X GDP(t-1)	0.00015 (0.60955)	0.00009 (0.62941)	0.00007 (0.58763)	0.00003 (0.23897)	0.00000 (0.00973)

	D6	D7	D8	D9	D10
Temperature	0.03972 (1.51174)	0.02712 (1.14979)	0.03506 (1.70893)	0.04305 (2.15003)	0.09693 (3.02031)
Temperature, Squared	-0.00083 (-1.11326)	-0.00061 (-0.91016)	-0.00107 (-1.83037)	-0.00151 (-2.65746)	-0.00319 (-3.54820)
Temperature X GDP(t-1)	-0.00362 (-1.28026)	-0.00224 (-0.88444)	-0.00307 (-1.39295)	-0.00392 (-1.82044)	-0.00945 (-2.73144)
Temperature Sq. X GDP(t-1)	0.00006 (0.65516)	0.00004 (0.49106)	0.00009 (1.31299)	0.00015 (2.18207)	0.00035 (3.25627)

T-statistics in parenthesis

Table A.4: BHM specification

Dependent Variables:	Decile income growth										GDP pc growth
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Temperature	0.0197	0.0198**	0.0180**	0.0184**	0.0166**	0.0159**	0.0158**	0.0158***	0.0167***	0.0203**	0.0173***
	(0.0138)	(0.0096)	(0.0084)	(0.0078)	(0.0070)	(0.0065)	(0.0062)	(0.0060)	(0.0064)	(0.0092)	(0.0060)
Temperature, Squared	-0.0008	-0.0006*	-0.0006**	-0.0006**	-0.0006***	-0.0006***	-0.0005***	-0.0005***	-0.0005***	-0.0005**	-0.0006***
	(0.0005)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
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
I(year$\hat{2}$) (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	5,636
R^2	0.11663	0.12564	0.13543	0.16150	0.19238	0.21901	0.24941	0.27367	0.27012	0.16750	0.29015
Within R^2	0.07007	0.01463	0.01155	0.01642	0.00548	0.00287	0.00376	0.00755	0.00587	0.03778	0.01561

Clustered (Country) standard-errors in parentheses

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

Table A.5: KW specification

Dependent Variables:	Decile income growth										GDP pc growth
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Δtemperature	0.0280*	0.0256**	0.0225**	0.0219**	0.0193**	0.0183***	0.0180***	0.0179***	0.0186***	0.0201**	0.0196***
	(0.0149)	(0.0107)	(0.0091)	(0.0084)	(0.0075)	(0.0069)	(0.0065)	(0.0063)	(0.0065)	(0.0089)	(0.0062)
Δtemperature, t-1	0.0020	0.0043	0.0030	0.0019	0.0012	0.0008	0.0009	0.0003	0.0003	0.0066	0.0009
	(0.0149)	(0.0093)	(0.0078)	(0.0071)	(0.0061)	(0.0052)	(0.0045)	(0.0039)	(0.0035)	(0.0069)	(0.0031)
Δtemperature, t *temperature, t-1	-0.0020*	-0.0016**	-0.0014**	-0.0015***	-0.0013***	-0.0013***	-0.0012***	-0.0012***	-0.0012***	-0.0011**	-0.0013***
	(0.0011)	(0.0007)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0003)
Δtemperature, t-1 *temperature, t-1	-0.0011	-0.0003	-0.0004	-0.0003	-0.0003	-0.0002	-0.0002	-0.0001	-6.35×10^{-5}	-0.0004	-0.0001
	(0.0013)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)
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	5,636
R^2	0.09281	0.08493	0.09396	0.11418	0.14116	0.16662	0.19690	0.22165	0.21954	0.13138	0.24088
Within R^2	0.06203	0.00865	0.00648	0.00919	0.00377	0.00546	0.01220	0.02054	0.01583	0.02845	0.03336

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

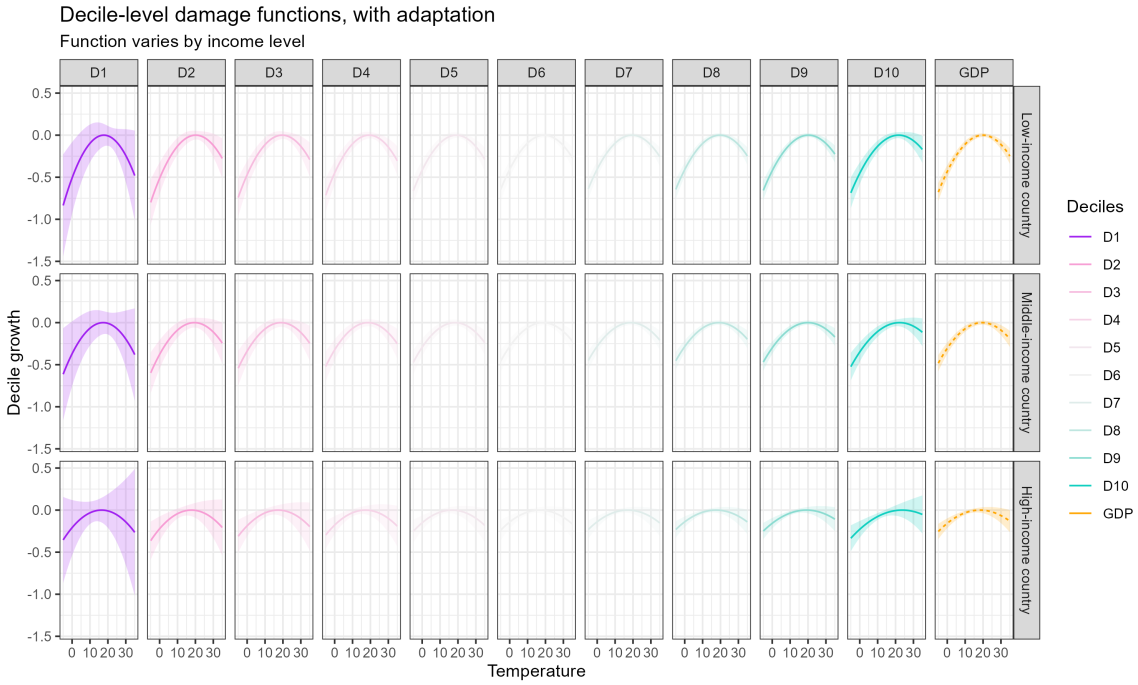


Figure A.1: Decile damage functions, with 90% confidence intervals at low, middle and high-income levels.

A.2 Comparing impacts with previous literature

Using novel subnational data, Kalkuhl and Wenz (2020) (KW) estimate the effect of temperature on Gross Regional Product (GRP), which they model as a function of both temperature changes and levels. We re-estimate KW with country-level data and project damages under SSP3 - RCP 7.0 (global warming of 3.1°C relative to the average between 1995 and 2015). By the end of the century, damages amount to approximately 2.4% of global per capita GDP. By contrast, using estimates from sub-national data, KW project damages of 7–14% under SSP2- RCP 8,5. The discrepancy should not necessarily come as a surprise, as the coefficients from a subnational analysis may not be directly ported to country-level damages. First, the number of sub-national units is not constant across countries; hence estimates reflect a different average effect. Second, the sum of subnational impacts need not coincide with country-level impacts if within-country spillovers or adaptation (e.g., through trade) exist. Figure A.2 plots the trajectory of projected damages under the quadratic form of Burke et al. (2015), the extension allowing for adaptation, and under the functional form of KW. We recover closely comparable damage estimates to KW's original paper, under a slightly different scenario (SSP3 - RCP 7.0 instead) when using their original coefficients and apply them to our country-level projections of temperature and GDP. Moreover, we obtain comparable damages to Burke et al. (2015) (≈17% damages at the global level) when using SSP5 - RCP 8.5 (the same warming scenario as in their original paper). Additional differences may come from updated real per capita GDP data from the World Bank, as well as updated weather data from the Climate Research Unit at the University of East Anglia.

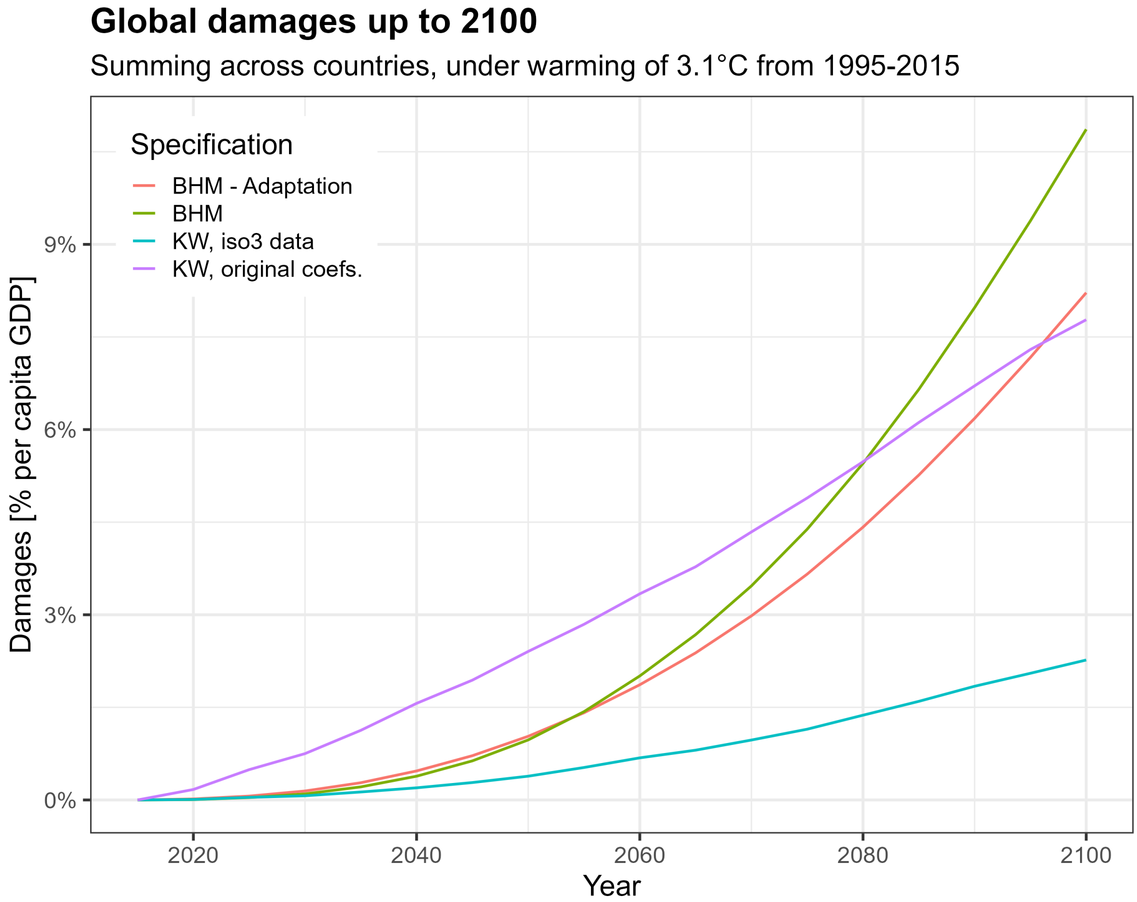
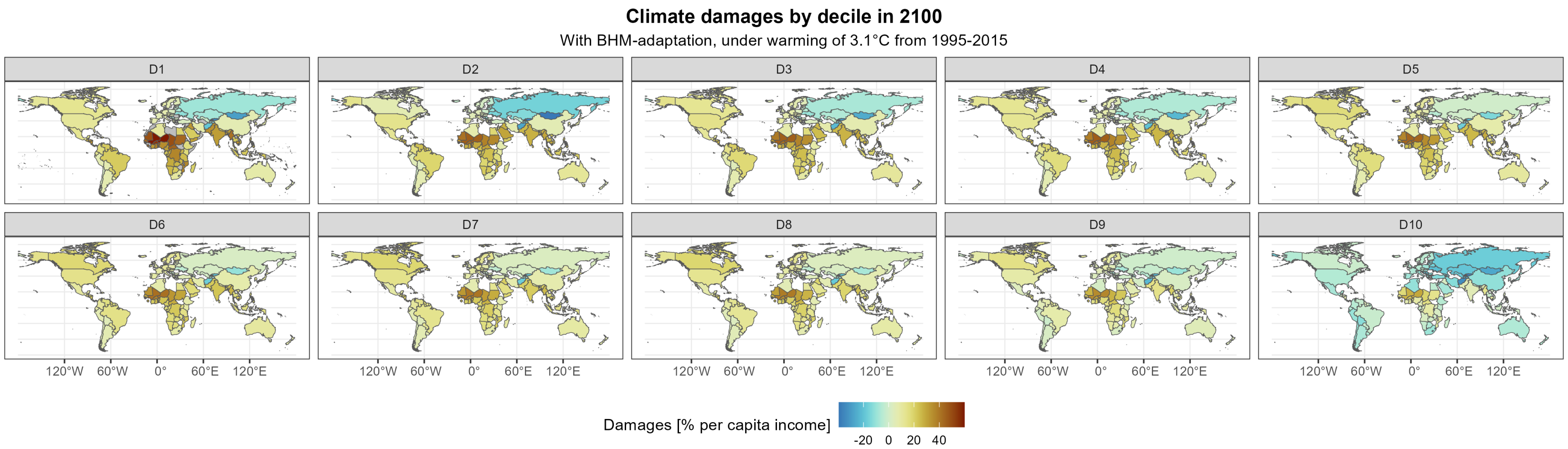


Figure A.2: Projected global damages as a share of global GDP. Damages are calculated from growth projections coming from RICE50+.

A.3 Projected distributional impacts - additional results


Climate damages by decile in 2100
With BHM-adaptation, under warming of 3.1°C from 1995-2015
D1
D2
D3
D4
D5
D6
D7
D8
D9
D10
120°W 60°W 0° 60°E 120°E
Damages [% per capita income]
-20 0 20 40

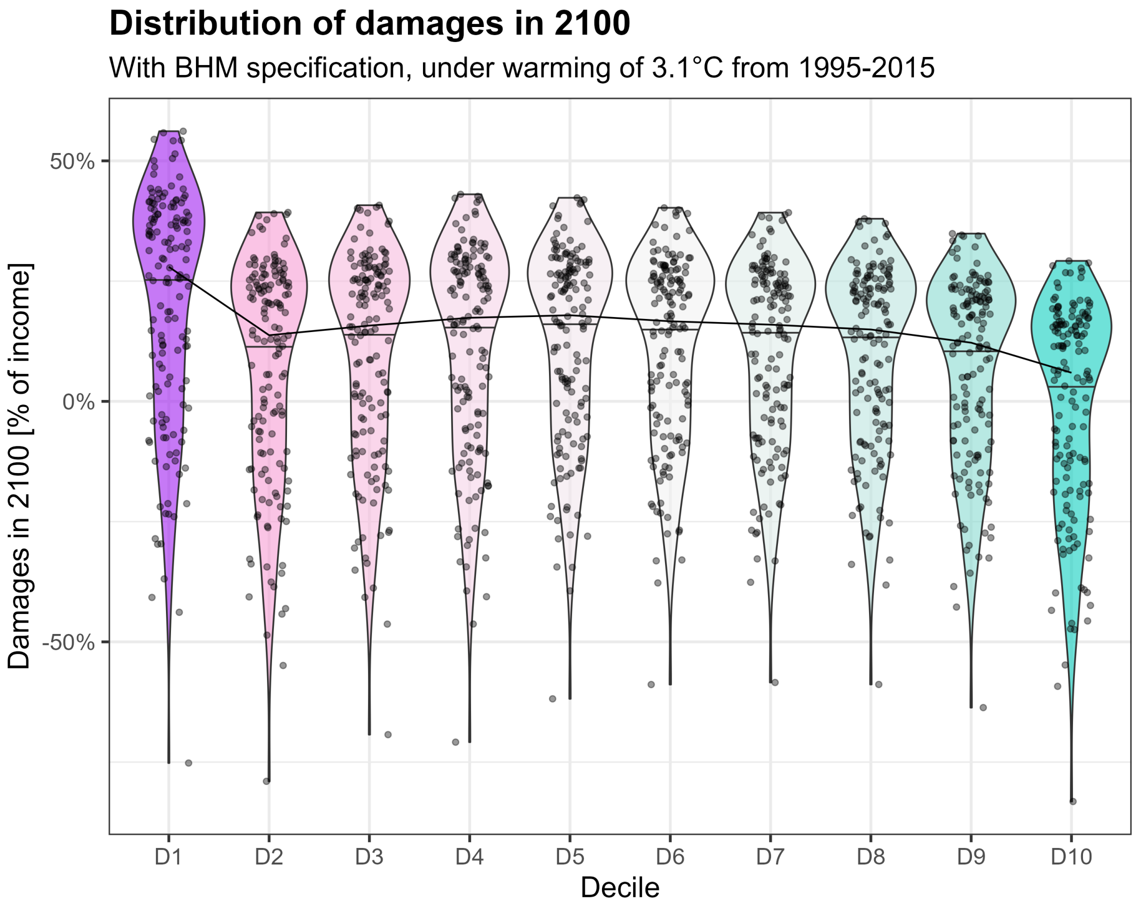


Figure A.4: Projected decile-level impacts in 2100, under the BHM specification. Each dot represents the projected impact on decile-level income for a given income decile in one of the 154 countries of RICE50+. The solid black line connects the median of the distribution, for each decile, of projected impacts across countries.

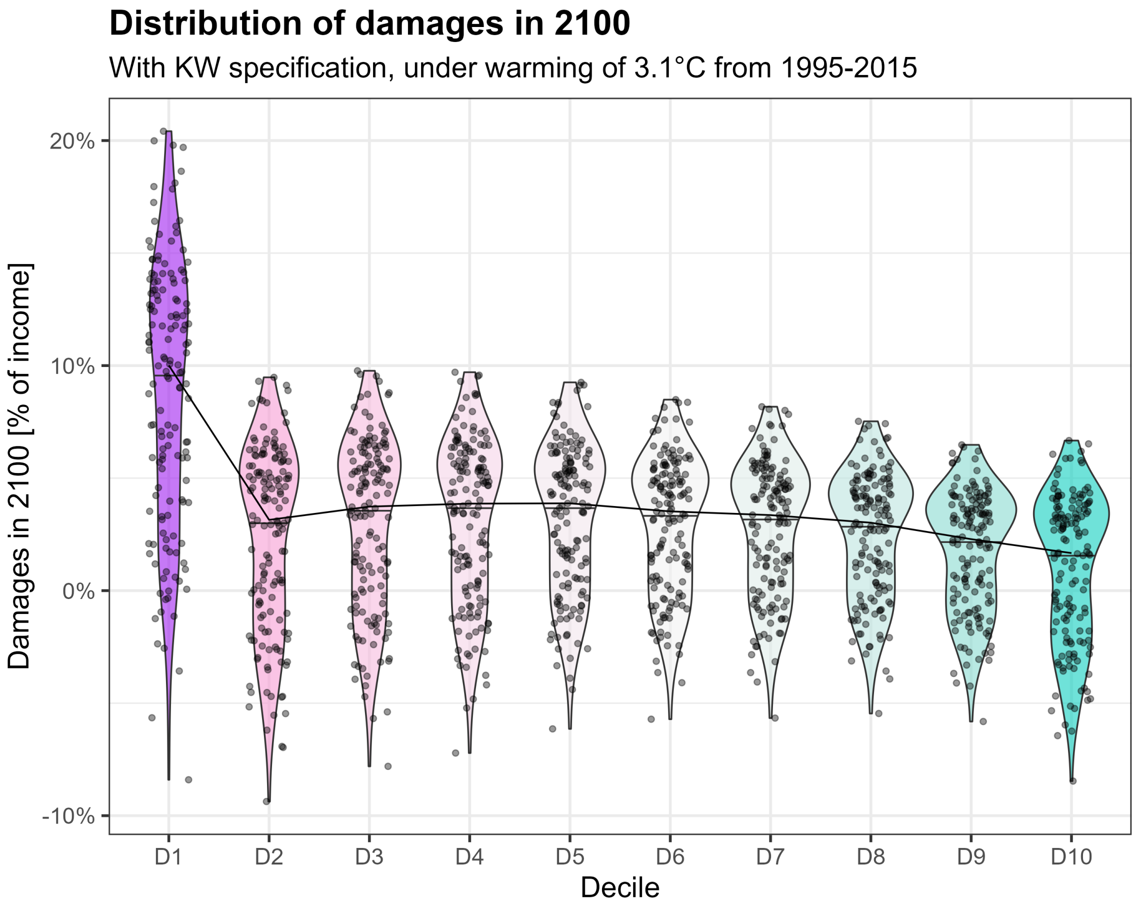


Figure A.5: Projected decile-level impacts in 2100, under the KW specification. Each dot represents the projected impact on decile-level income for a given income decile in one of the 154 countries of RICE50+. The solid black line connects the median of the distribution, for each decile, of projected impacts across countries.

A.4 Income elasticity of impacts

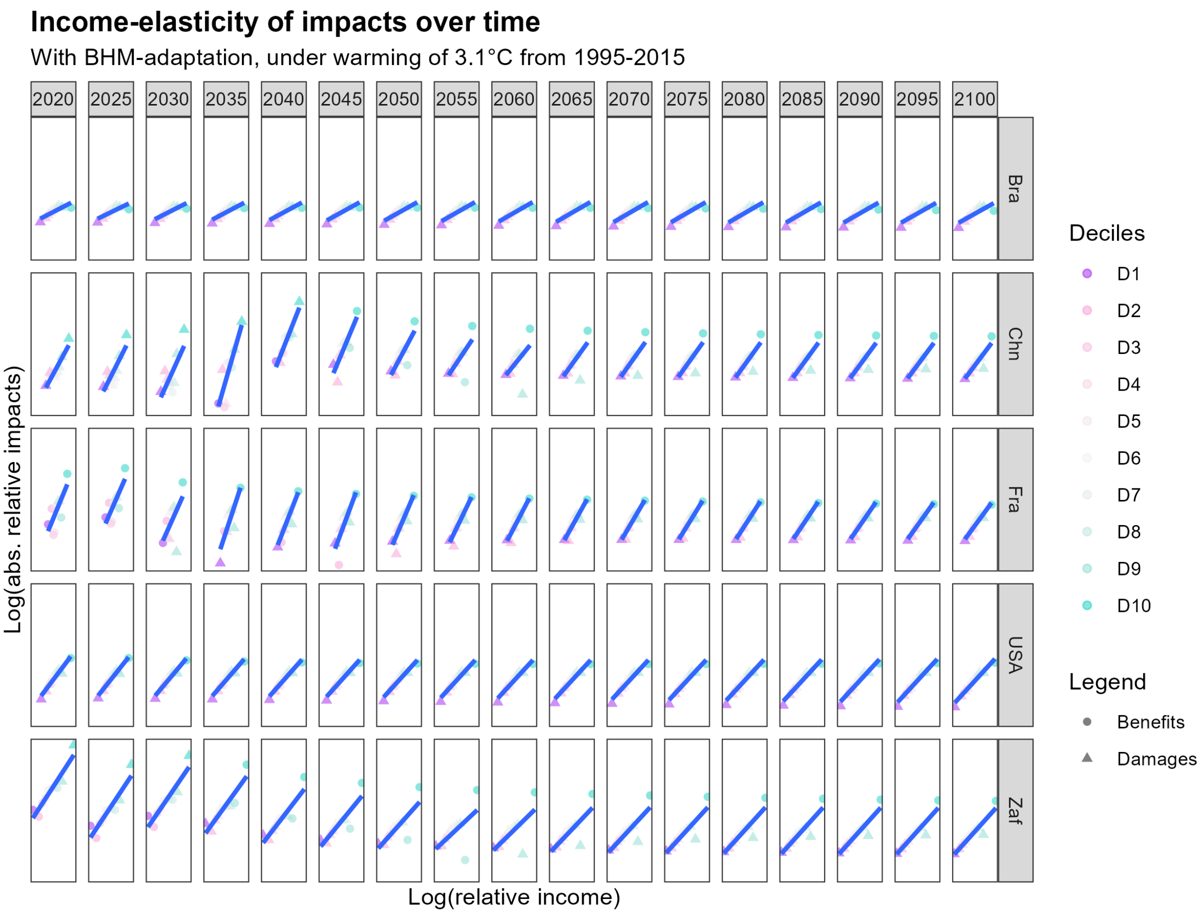


Figure A.6: Income Elasticity of impacts over time, selected countries

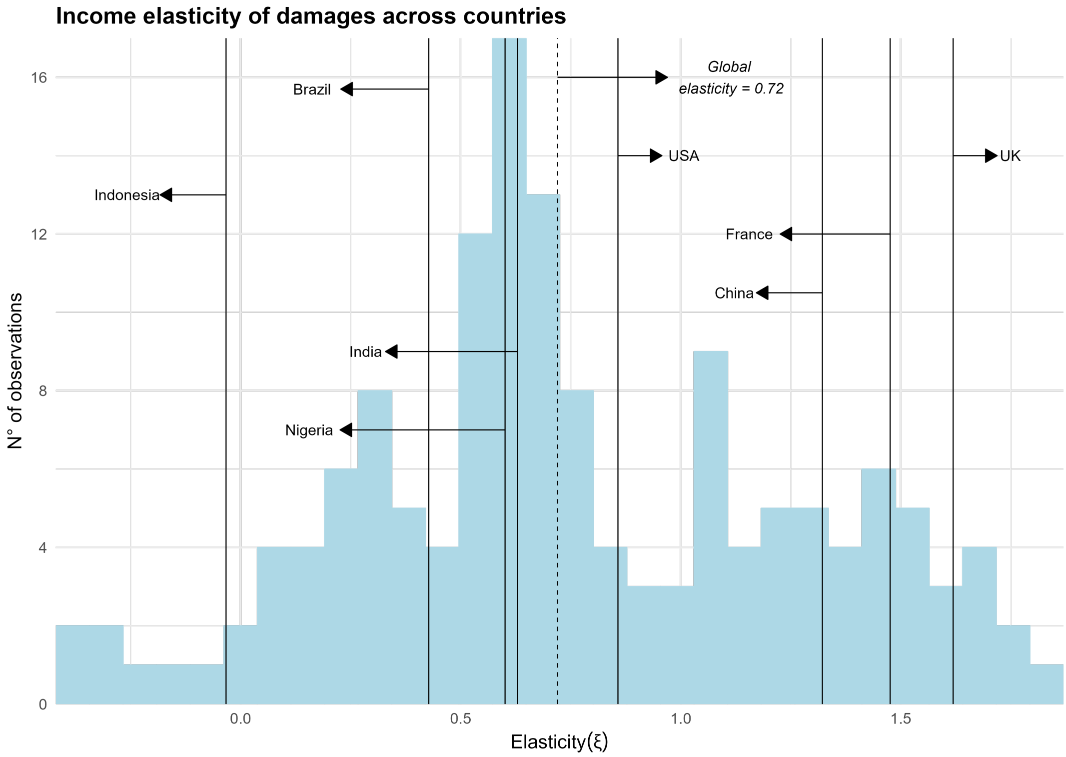


Figure A.7: Income Elasticity of impacts across countries

A.4.1 Robustness to choice of fixed effects

Table A.6: Income elasticity of impacts, under BHM specification

Dependent Variable:	Relative climate damages			
Model:	(1)	(2)	(3)	(4)
Variables				
Relative income	0.8407***	0.8418***	0.8405***	0.8417***
	(0.0055)	(0.0055)	(0.0249)	(0.0052)
Fixed-effects				
Time		Yes		Yes
Country			Yes	Yes
Fit statistics				
Country	23,680	23,680	23,680	23,680
R^2	0.49583	0.49674	0.58575	0.58666
Within R^2		0.49668	0.53567	0.53661

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

Table A.7: Income elasticity of impacts, under BHM - Adaptation specification

Dependent Variable:	Relative climate damages			
Model:	(1)	(2)	(3)	(4)
Variables				
Relative income	0.7195***	0.7179***	0.7202***	0.7186***
	(0.0073)	(0.0021)	(0.0380)	(0.0018)
Fixed-effects				
Time		Yes		Yes
Country			Yes	Yes
Fit statistics				
Country	23,680	23,680	23,680	23,680
R^2	0.29222	0.29469	0.39558	0.39805
Within R^2		0.29180	0.31841	0.31805

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

Table A.8: Income elasticity of impacts, under KW specification

Dependent Variable:	Relative climate damages			
Model:	(1)	(2)	(3)	(4)
Variables				
Relative income	0.6891***	0.6883***	0.6935***	0.6927***
	(0.0066)	(0.0053)	(0.0222)	(0.0042)
Fixed-effects				
Time		Yes		Yes
Country			Yes	Yes
Fit statistics				
Country	23,680	23,680	23,680	23,680
R^2	0.31817	0.31880	0.47100	0.47163
Within R^2		0.31762	0.37003	0.36948

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

A.4.2 Robustness to excluding positive climate impacts

Table A.9: Estimates of the income elasticity of climate damages, excluding positive climate impacts

Dependent Variables:	Relative damages - BHM	Relative damages - BHM adapt.	Relative damages - KW
Model:	(1)	(2)	(3)
Variables			
Relative income	0.8496***	0.6951***	0.6987***
	(0.0053)	(0.0053)	(0.0055)
Fixed-effects			
Time	Yes	Yes	Yes
Country	Yes	Yes	Yes
Fit statistics			
Country	22,552	21,494	22,230
R^2	0.66825	0.42652	0.52768
Within R^2	0.63344	0.34943	0.45451

Clustered (Time) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

A.5 Global results across scenarios

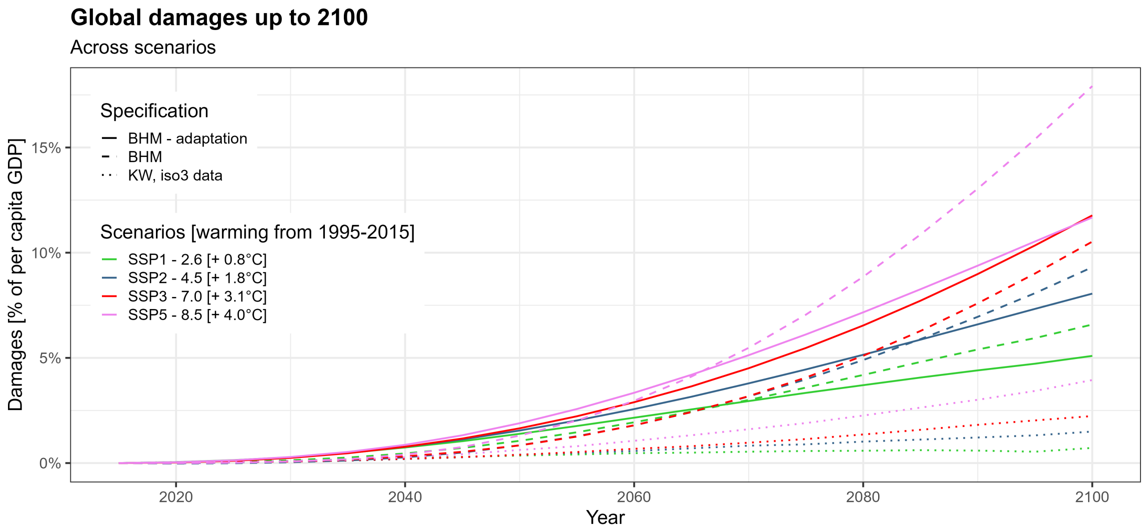


Figure A.8: Global damages, all RCP-SSP scenarios

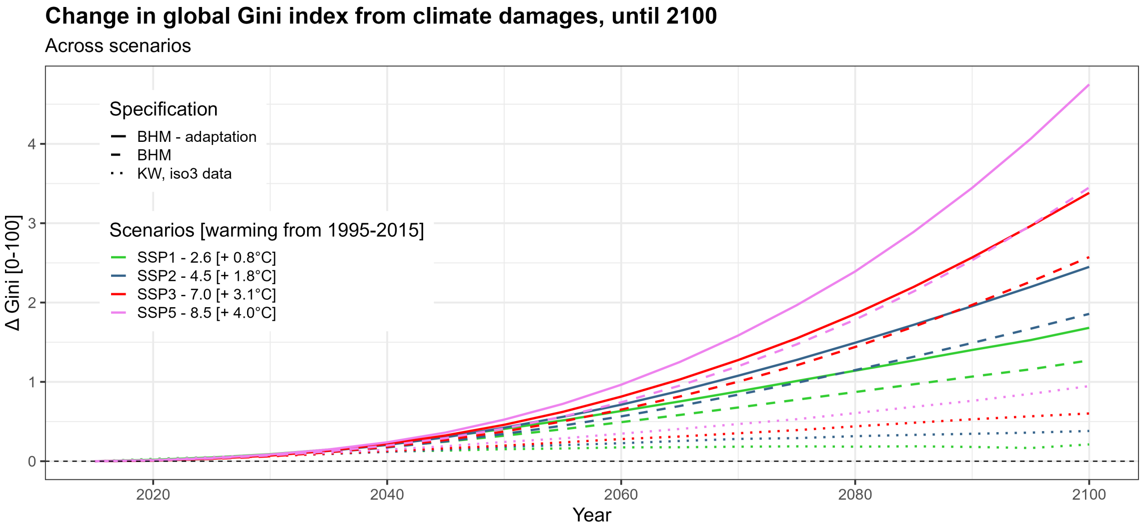


Figure A.9: Global Gini impacts, all RCP-SSP scenarios