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A multi-model assessment of inequality and climate change

In the format provided by the authors and unedited

Supplementary Information

A: Implementation of inequality in the different models

Model	*Type*	*Regional Focus*	*Sources of inequality*	*Modelling of Distribution*	*Measure of Distribution*	*Mitigation distribution*	*Impact Distribution*
AIM	DP-IAM	Global, 184 countries	Price change, Consumption patterns	soft-linked poverty, household and income distribution model	Deciles Gini index	All goods Carbon revenues	-
E3ME	Econometric	71 regions	Price changes, unemployment, structural change	Endogenous	Quintiles, employed, unemployed, self-employed (14 groups)	All goods Employment (Quintiles have been just downscaled to Deciles)	-
GEM-E3	CGE	Global 20 regions, EU country level	income, price changes, savings, consumption patterns, structural change	soft-linked inequality module with GEM-E3	Deciles	All goods Energy expenditures Carbon revenues	-
Imaclim	CGE	Global, 12 regions	Consumption shares	Exogenous module, endogenous integration	regional Gini, Deciles	Elasticity of mitigation costs (based on [1]) Carbon revenues	-
NICE	CB-IAM	Global 12 regions	Consumption shares	Regional distribution + income elasticities	Deciles	Elasticity of mitigation costs (based on [1]) Carbon revenues	Income elasticity of damage function (=1) with RICE damage function
ReMIND	DP-IAM	Global, 12 regions	energy expenditures, impacts	regional distribution	Lognormal distribution	Elasticity of energy expenditures, Carbon revenues	Aggregate GDP damage function[2] with income elasticity of 0.5
WITCH	DP-IAM	Global, 17 regions	Capital ownership Wages Energy consumption shares	soft-linked inequality model with WITCH	Deciles Gini	Energy expenditures (based on individual HH surveys) Carbon revenues	-
RICE50+	CB-IAM	Global 57 regions	Consumption shares	Regional distribution + income elasticities	Deciles	Elasticity of mitigation costs (based on [1]) Carbon revenues	Income elasticity of damage function (=0.5) and damage function[2]

Note: DP: detailed-process based, CB = Cost-Benefit, CGE = Computable General Equilibrium model

Table S1: List of models participating in this study.

AIM: AIM implements the consumption distribution assessment by soft-linking a poverty, household and income distribution modelling tool called the AIM/PHI to a CGE model (AIM/Hub). The poverty, household, and income distribution modelling tool embody a lognormal assumption and a nonlinear demand system[3,4]. The lognormal distribution captures the national average household consumption in the CGE and matches the Gini projections by Rao et al[5]. The distributional effects of climate policies are introduced by passing the commodity prices to the AIDADS model, where the household consumption patterns in each country are calibrated to global and national household consumption survey databases. Carbon tax revenues redistribution is modelled in the CGE as a lump-sum transfer to the representative household, but it is then altered in AIM/PHI. In the default mitigation scenario, all households in AIM/PHI have the same change ratio as national average household consumption, which is already compensated by the lump-sum transfer. In the EPC redistribution scenario, consumption without the compensation from the lump-sum transfer is firstly distributed to households in AIM/PHI. We then compensate the household individually on an EPC basis, and calculate the Gini, which depicts the inequality after an EPC redistribution.

E3ME: In E3ME-FTT, the GINI coefficient is computed from disposable incomes before social transfers. The method is expenditure-based and does not include differential changes in sectoral employment. A further limitation is that the method does consider how income groups differ in their response to higher (energy) prices, for instance by insulating homes. The data for EU countries is based on equivalized disposable income before social transfers from Eurostat, whereas data outside of the EU is based on World Bank development indicators. E3ME runs only until 2050, and the inequality parts are run only for European countries, hence only results for France are reported in this comparison exercise.

GEM-E3: In GEM-E3, the Gini index is computed from disposable incomes before social transfers. The method to represent multiple households in GEM-E3 is based on the soft-linkage of the standard CGE model with a single representative household with a satellite module with multiple households (representing ten income deciles), through a sequential exchange of prices, incomes and demands until an equilibrium is established[6]. The satellite module is first calibrated using the aggregate consumption, wage and non-wage income, population and labour demand and supply of the GEM-E3 model and the distribution data by decile. Then, GEM-E3 projects total income, sectoral production, end-user prices and demand for skills until 2050. Total wage and non-wage income, transfers, prices of goods and services, wages by skill and skill requirements are passed on to the satellite model to compute the income and consumption for income deciles and estimate the impacts on different households. Then, the consumption by decile is aggregated to the single representative household and is plugged into GEM-E3 where a new set of prices and wages are computed. This loop continues until the change in prices and demand is below a certain threshold ensuring general equilibrium. The satellite model aggregates households in 10 income classes with different income sources, consumption and saving patterns. The equivalized household size by decile and the type of labour skills supplied by each decile are assumed to remain constant. The link between skills, sectoral activity and income deciles depends on the skills acquired by each household and the evolution of sectoral production. The analysis of climate policy impacts on energy poverty may require a finer resolution of individual households to capture the effects at the tales of the distribution, but data are not available at more granular level [6].

Imaclim: In Imaclim, we calibrate baseline deciles over time using country income Gini projections until 2100 in the SSP2 scenario[5], and using GDP and population data for year 2014 from the World Bank Development Indicators database (GDP is expressed in constant 2015 USD, population in number of individuals). We assume that for each country, income is distributed across deciles according to a lognormal distribution. We can deduce standard deviations from country Gini indices,

and then a Lorenz curve for each country and each time step. The Lorenz curve represents the share of overall income, consumption or wealth detained as a function of the cumulative share of the population. We then aggregate country Lorenz curves into regional Lorenz curves, following the regional definition of the model (12 world regions in the case of Imaclim). In the case of country regions (US, Canada, India, China, Brazil), we directly use the Lorenz curves deduced from the income Gini indices available in (Rao et al., 2019). The regional consumption deciles obtained from the calibration are then fed into the model. They are modified depending on the climate scenario considered. Mitigation costs and carbon tax burdens are distributed across deciles using consumption elasticities. The initial burden of a carbon tax is the distribution of mitigation costs and carbon tax payments before tax revenues are recycled and redistributed. We follow the approach of Budolfson et al[1] and write total consumption C_{rjt} of decile j in region r and at date t as$C_{rjt} = C_{rt}^{gross} \cdot q_{rjt} - C_{rt}^{gross} \cdot \lambda_{rt} \cdot \tau_{rjt} + E_{rt} \cdot tax_t \cdot \delta_{rjt}$. The first term is total gross consumption of decile j. Total baseline (gross) consumption of region r at date t is noted C_{rt}^{gross}. The second term is the mitigation cost. The third term is tax repayment. E_{rt} is the emissions from region r at date t, $E_{rt} \cdot tax_t$ is the carbon tax revenue from region r at date t. Within each country, mitigation costs (i.e., the initial burden) are assumed to be distributed across deciles using the same consumption elasticity for a given country at a given time (τ_{rjt}). Consumption elasticities of the initial burden depend on regional GDP per capita at each time step and are calibrated based on a review of the literature on the initial burden of carbon taxation across countries before the redistribution of tax revenues. The distributional weights τ_{rjt} are calculated as a function of the consumption elasticity of the initial burden $w_{r,t}$ as (recall that n_q is the number of quantiles) $\tau_{rjt} = n_q \cdot q_{rjt}^{w_{rt}} / \sum_k q_{rkt}^{w_{rt}}$.
Finally, the value of δ_{rjt} determines the mode of carbon tax revenue recycling. If we set $\delta_{rjt} = 0$, the recycling of carbon tax revenues does not alter the initial burden distribution, and we have $C_{rjt} = C_{rt}^{gross} \cdot q_{rjt} - C_{rt}^{gross} \cdot \lambda_{rt}\tau_{rjt}$. If we set $\delta_{rjt} \neq 0$, the recycling of carbon tax revenues alters the initial burden distribution, and we have $C_{rjt} = C_{rt}^{gross} \cdot q_{rjt} - C_{rt}^{gross} \cdot \lambda_{rt}\tau_{rjt} + E_{rt} \cdot tax_t \cdot \delta_{rjt}$.
In the case of equal per capital recycling, we set $\delta_{rjt} = \frac{1}{n_q}$.

NICE: We use the same calibration steps as described in the case of Imaclim (above) to obtain baseline consumption deciles over time in the NICE model. The regional consumption deciles obtained from the calibration are then fed into the model. Mitigation costs and carbon tax burdens are distributed across deciles using consumption elasticities. The initial burden of a carbon tax is the distribution of mitigation costs and carbon tax payments before tax revenues are recycled and redistributed. The modelling steps are described in the methods section of Budolfson et al[1]. We assume that, within a region, the mitigation costs and the tax payments are distributed according to the same weights across deciles. Using the same notations as above, we write total consumption of decile j in region r at date t as $C_{rjt} = C_{rt}^{gross} \cdot q_{rjt} - C_{rt}^{net} \cdot D_{rt} \cdot d_{rjt} - C_{rt}^{gross} \cdot \lambda_{rt} \cdot \tau_{rjt} - E_{rt} \cdot tax_t \cdot \tau_{rjt} + E_{rt} \cdot tax_t \cdot \delta_{rjt}$. $C_{rt}^{net} \cdot D_{rt} \cdot d_{rjt}$ is the damage cost of decile j of region r at date t. Carbon tax revenues are either refunded within each region according to the distribution of the initial burden ($\delta_{rjt} = \tau_{rjt}$) or are distributed equally per capita within each region ($\delta_{rjt} = \frac{1}{n_q}$).

ReMIND: ReMIND implements the consumption distribution using a log-normal assumption. The distribution in each region is calibrated so that average consumption matches a baseline SSP2 consumption path and future inequality matches the Gini projections by Rao et al[5]. The effects of climate policy, redistribution and climate impacts on the consumption distribution is then calculated via changes in energy expenditure compared to the baseline, carbon tax revenue redistribution and the effects of climate damages. The elasticity of energy expenditures is estimated through an empirical approach, described in Soergel et al[7]. The elasticity of damages is assumed to be 0.5, damages are based on Kalkuhl and Wenz[2]. The tax revenues are redistributed either uniformly or on an equal per capita basis, determined by an elasticity parameter. The resulting new distribution is approximated to be lognormal, with the new average consumption and variance, by keeping the first and second moment of the distribution.

RICE50+: We implemented income deciles based on a baseline specification[5], and climate policy costs and climate impacts are distributed from the macrolevel among household deciles based on income elasticities[8]: Policy costs, computed using calibrated marginal abatement cost curves, are distributed using an elasticity that varies with GDP per capita[1], while impacts, that are computed used the damage function[2] are distributed using an elasticity of 0.5.

WITCH: The WITCH model implemented the climate policies based on its bottom-up energy system model including land-use coupling with GLOBIOM. The model results are then in terms of energy expenditures, energy prices, and GDP fed into a soft-coupled "inequality module"[9], where a dynamic household optimization problem is solved using the inequality dataset described in part A and taking into account energy expenditures, wealth inequality, heterogeneous wages, returns on capital, and savings, resulting in an endogenous distribution of income and consumption consistent with the macroeconomic results from WITCH.

B: The NAVIGATE inequality dataset at the income decile level for use in IAMs

A standardized input data template has been defined and data has been collected using household surveys from a number of developed and OECD countries.

Available countries (for the latest year, between 2008 and 2017, available):

- India, Brazil, France, South Africa, United States of America, China, Mexico
- 26 EU member states based on a common survey.

The data is all structured around income deciles. Units of observations for the deciles are households. The OECD modified equivalence scale has been applied to compute household income per person. (1 plus 0.5 per adult (older than 14 years) and 0.3 per child (14 or less years)). Note this definition differs slightly from the OECD's original definition where adults are 14 years and older. This has been chosen since many demographic projections report populations by age cohorts of five years, so we consider 15+ years old as adults.

Available variables (all for deciles D1 to D10):

- Income share
- Expenditure share
- Expenditure share in

- Energy for Transportation
- Energy for Housing
- Food

- Education of the household head
- Average savings rate
- Household size
- Income by type (labour, capital, transfers, other)
- Wealth share (where available)

The dataset is available at https://github.com/witch-team/NAVIGATE-inequality-dataset.

The energy expenditure shares for housing and transportation are key variables for IAMs, and here the expenditure shares across countries, which show a strong regressive pattern for residential energy consumption while for transportation it appears in most countries to be progressive.

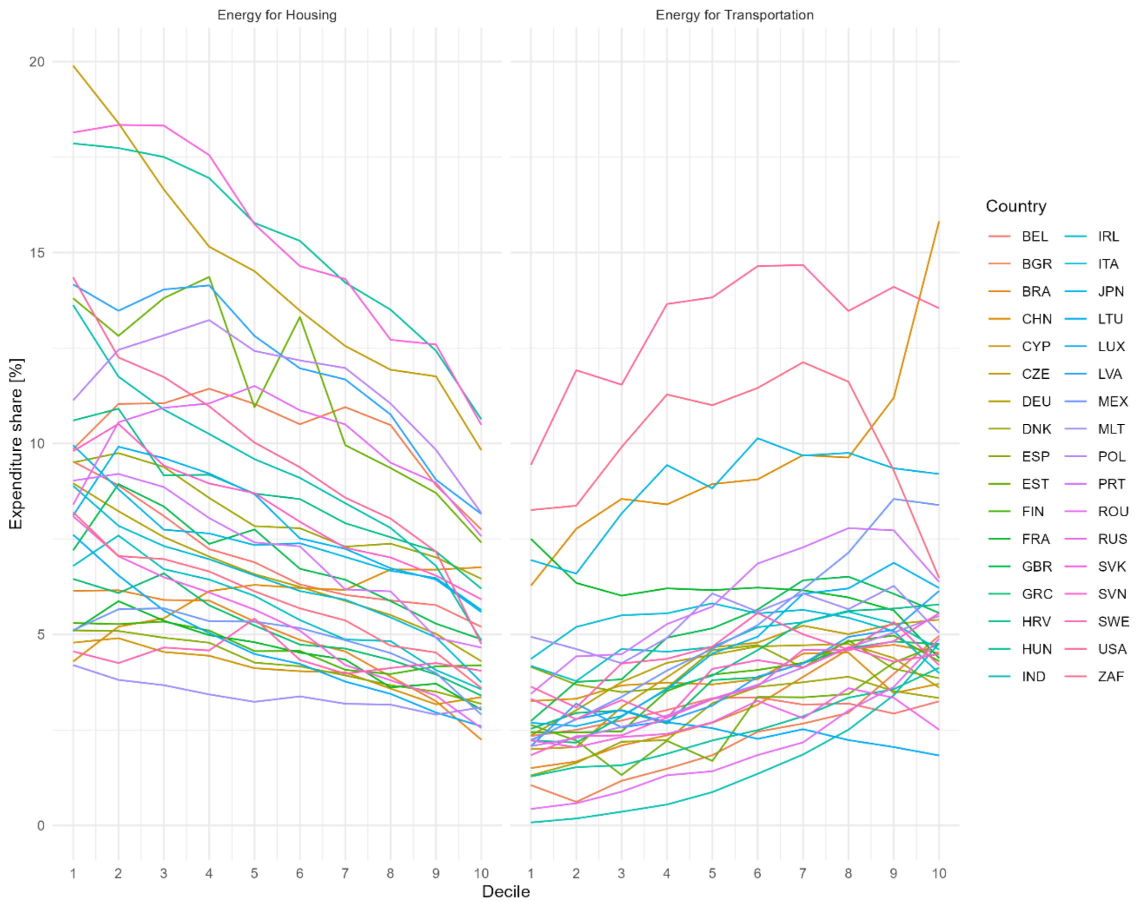

Figure S1: consumption shares of energy for housing and transportation based on the inequality dataset for all countries and across deciles.

Household survey data sources:

- Brazil: Consumer Expenditure Survey from IBGE (2009): "Pesquisa de Orçamentos Familiares 2008-2009 - Despesas, Rendimentos e Condições de Vida,"Technical report, Rio de Janeiro, Brazil, for the year 2008. Retrieved from https://portaldeboaspraticas.iff.fiocruz.br/biblioteca/esquisa-de-orcamentos-familiares-2008-2009/
- Mexico: 2018 wave, National Survey of Household Income and Expenditure (ENIGH). The National Institute of Statistics, Geography and Informatics (INEGI). Retrieved from https://en.www.inegi.org.mx/programas/enigh/nc/2018/
- Russia: 2019 wave, Russia Longitudinal Monitoring Survey (RLMS-HSE). Higher School of Economics and ZAO "Demoscope" together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology RAS. Retrieved from https://rlms-hse.cpc.unc.edu
- India: 2012 wave, National Sample Survey 2011-2012 (68th round) - Consumer Expenditure. Ministry of Statistics & Programme Implementation, Government of India. Retrieved from http://microdata.gov.in/nada43/index.php/catalog/1
- China: Chinese Household Income Project, 2013 wave (CHIP) – CHIP Dataset Homepage. Retrieved from http://www.ciidbnu.org/chip/index.asp
- United States of America: US Consumer Expenditure Surveys, 2019 wave (CE) - Consumer Expenditure Surveys Public Use Microdata (PUMD). Retrieved from https://www.bls.gov/cex/pumd.htm
- South Africa: South Africa National Income Dynamics Study, waves 1-5 (NIDS) - NIDS Data Access. Retrieved from http://www.nids.uct.ac.za/nids-data/data-access
- EU member states: EUROSTAT Household Budget Surveys (HBS) for all EU member states (plus Serbia and the United Kingdom), latest full wave from 2010, Retrieved from https://ec.europa.eu/eurostat/web/household-budget-surveys/overview
- France: Household Budget Survey (Budget de Famille, BdF) from INSEE for the year 2011, Retrieved from: https://www.insee.fr/fr/statistiques/2015691

C: Additional results and figures

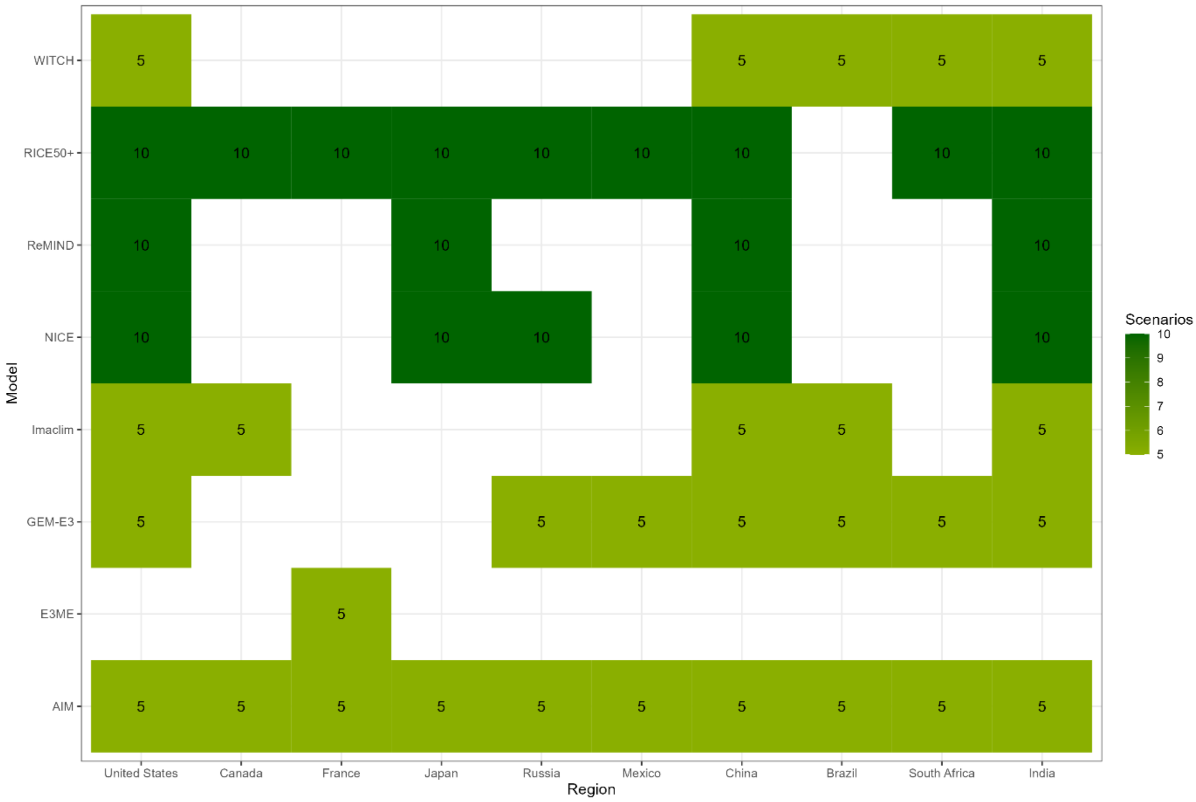

Figure S2: Models and regional coverage of the data used in this analysis

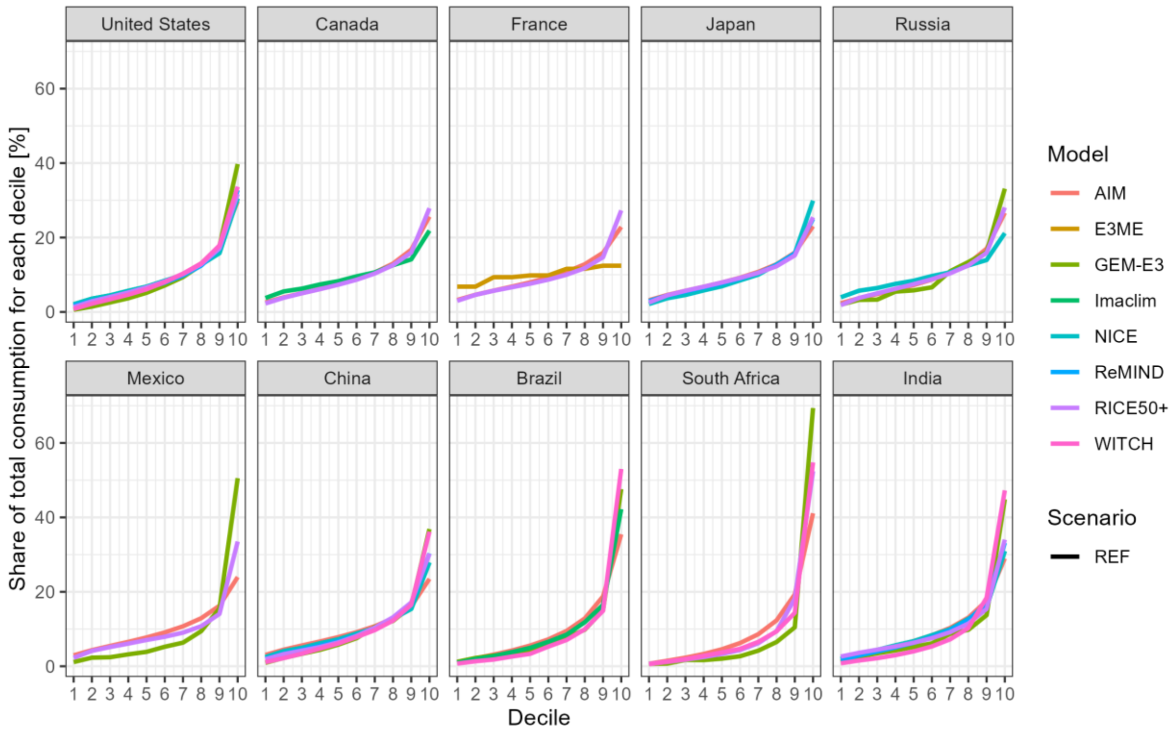

Figure S3: Consumption share for income deciles across countries in 2050

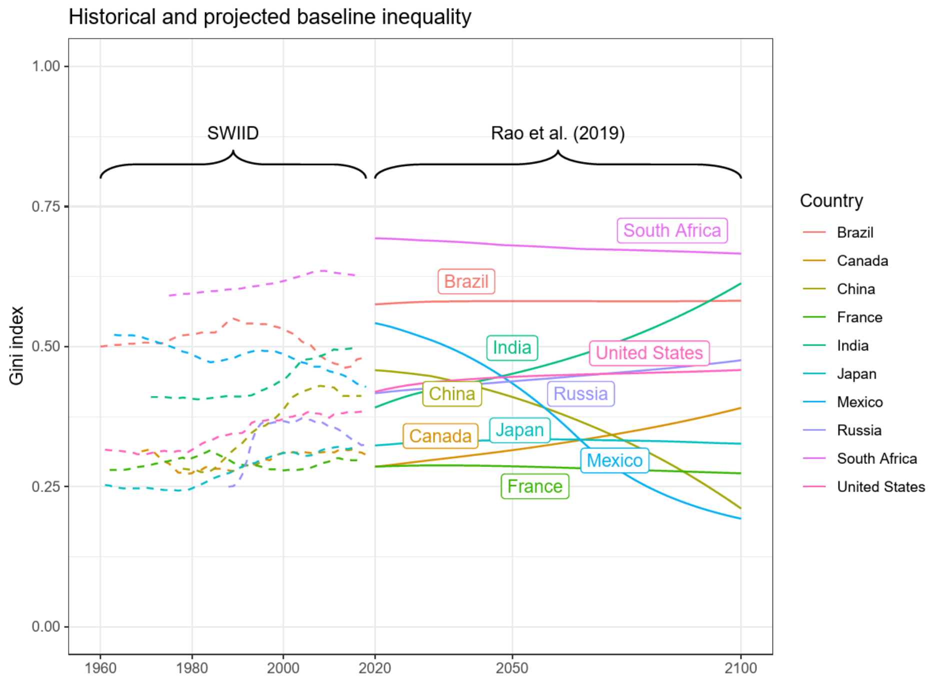

Figure S4: The Gini index of income inequality in the countries of this study. Dashed lines show the historical values based on the Standardized Income Inequality Database (SWIID) and the solid lines the baseline SSP2 projections from Rao et al. (2019).

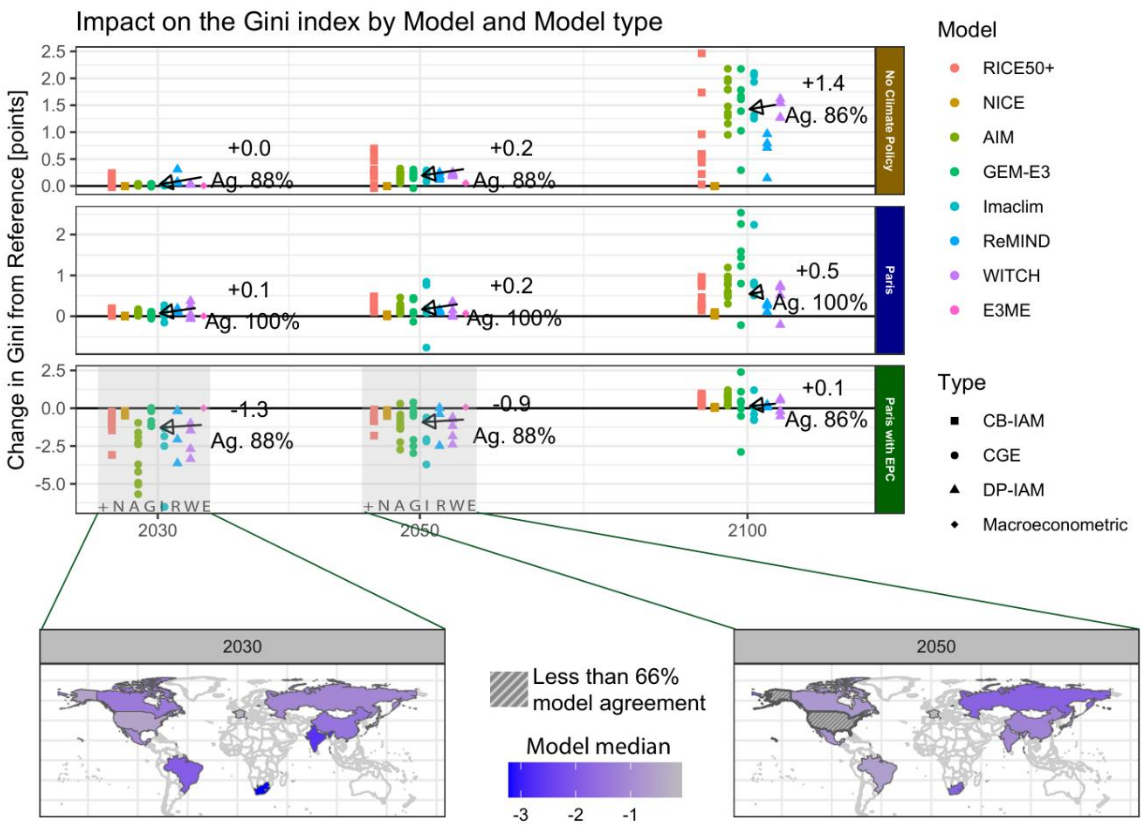

Figure S5: Gini impact for the Weak Paris set of scenarios (1150 $GtCO_2$)

	Dependent variable:
	Gini impact [points]
Change in temperature	0.423*** (0.009)
E3ME	−0.121*** (0.042)
GEM-E3	0.008 (0.013)
Imaclim	0.039*** (0.014)
NICE	−0.374*** (0.021)
ReMIND	−0.072*** (0.022)
RICE50+	−0.087*** (0.016)
WITCH	0.038*** (0.014)
Constant	0.054*** (0.010)
Observations	2,942
R^2	0.455
Adjusted R^2	0.454
Residual Std. Error	0.243 (df = 2933)
F Statistic	306.695*** (df = 8; 2933)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S2: Regression of the Gini impact (points) due to climate damages on the change in country-level temperature from today's level (°C) and model. The Gini impact is computed as difference between the Reference scenario with and without impacts. The reference category is the AIM model. Standard errors are given in the parenthesis and significance level is based on a one-sided standard t-test.

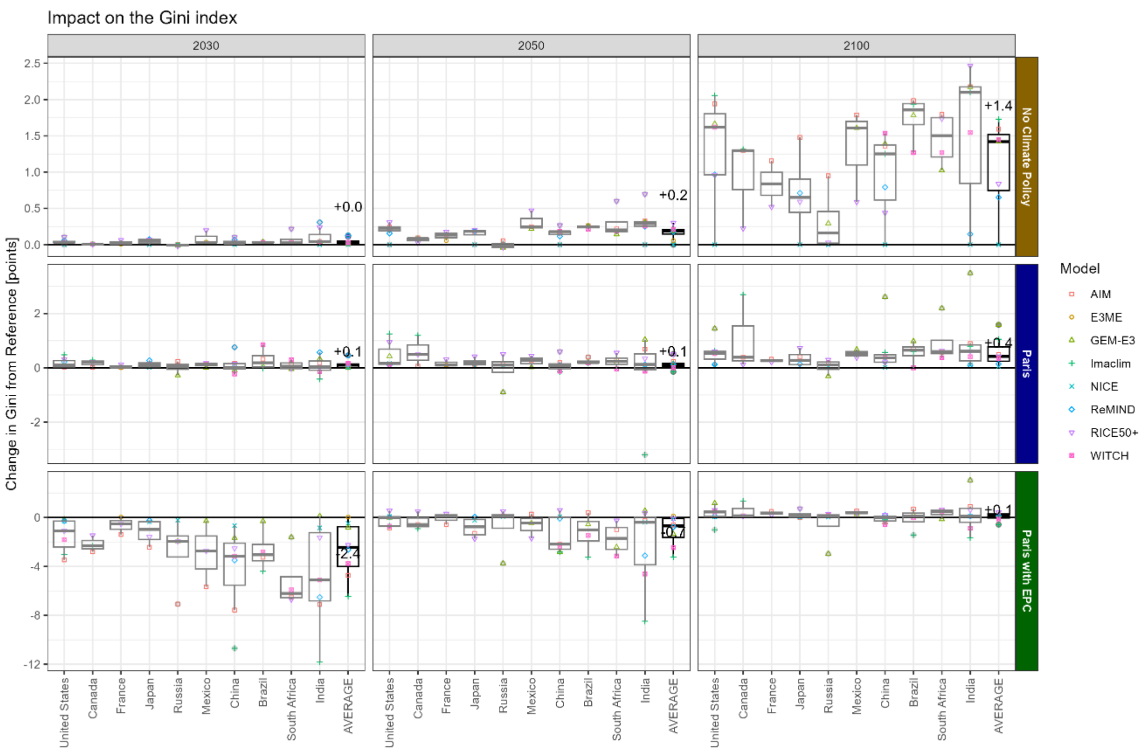

Figure S6: Country-specific change in the Gini index from the reference scenario (in points). The top row shows the impact of climate impacts in the Reference scenario, the middle row shows the Paris scenario, and the bottom row includes EPC redistribution. The points show the individual model results, and the boxplot shows the median, inter-quartile range (box), and values within 1.5 times the IQR (whiskers).

	Dependent variable:
	Change in decile income, from policy
Deciles under Reference scenario	1.029*** (0.033)
E3ME	−2.292** (1.085)
GEM-E3	−0.975*** (0.104)
Imaclim	1.144*** (0.107)
NICE	−1.498*** (0.112)
RICE50+	0.206** (0.090)
ReMIND	−0.153 (0.118)
WITCH	−0.351*** (0.112)
Brazil	0.640*** (0.131)
Canada	0.269** (0.134)
China	0.719*** (0.107)
France	−0.413*** (0.158)
India	0.948*** (0.119)
Japan	0.025 (0.123)
Mexico	0.175 (0.142)
Russia	1.196*** (0.126)
South Africa	1.072*** (0.139)
2025	6.468*** (0.149)
2030	7.001*** (0.150)
2035	7.189*** (0.149)
2040	7.375*** (0.150)
2045	7.498*** (0.150)
2050	7.568*** (0.150)
Constant	−11.374*** (0.386)
Observations	2,834
R^2	0.666
Adjusted R^2	0.664
Residual Std. Error	1.519 (df = 2810)
F Statistic	244.100*** (df = 23; 2810)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S3: Regressions of the pooled sample of all years 2020-2050, countries, and models to estimate the income elasticity of climate policy incidence. The dependent variable is the log of the change in income from the Reference to Paris scenario (wherever it is negative, which holds true for 87% of all observations in the sample), while the main independent variable is the log of income of a given decile, so that the coefficient yields an income elasticity of policy costs at the decile level. The reference category is the United States, the AIM model, and the year 2020. Standard errors are given in the parenthesis and significance level is based on a one-sided standard t-test.

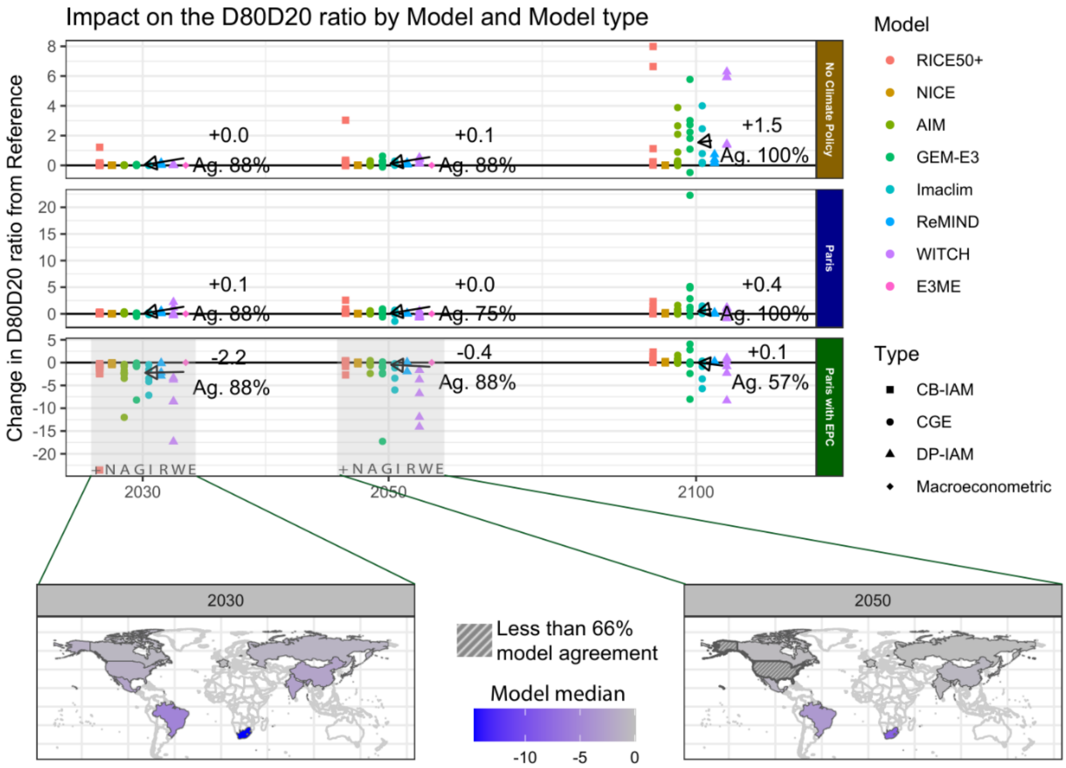

Figure S7: Impact on the D80D20 measure of inequality, the ratio between the income of the 20% richest and 20% poorest parts of the population.

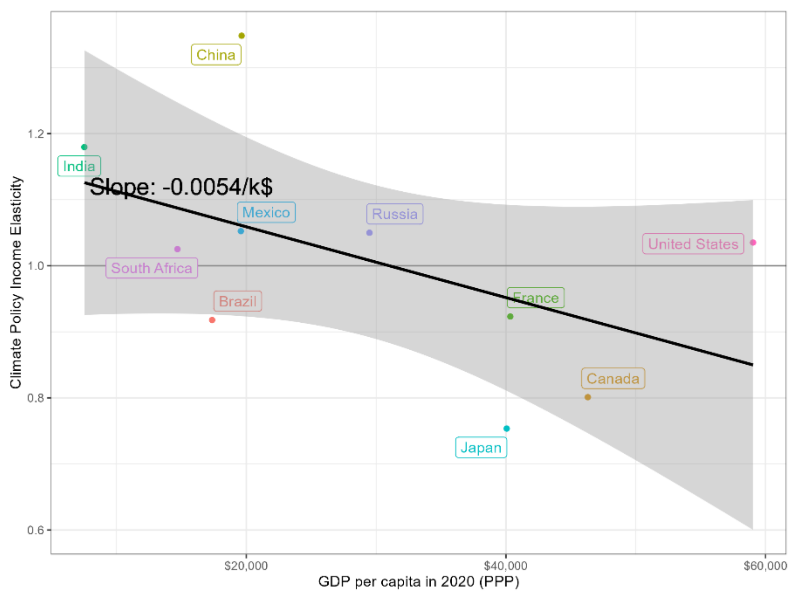

Figure S8: Estimated income elasticity of climate policy incidence per country, the x-axis shows the GDP per capita in 2020. The regression line shows the estimated relationship between the income elasticity and GDP per capita, across all models and over time. The shaded confidence band shows the 95% confidence level interval from a linear model fit.

Model	Average elasticity	Slope in GDP per capita across regions	Statistical significance of the slope (p-value of t-test)
AIM	0.96	0.002	0.03*
GEM-E3	1.00	-0.0033	0.69
Imaclim	1.03	-0.0123	0.01*
NICE	0.90	-0.0064	0.01*
RICE50+	0.94	-0.0068	0.00***
ReMIND	0.84	-0.0053	0.15
WITCH	1.09	-0.0037	0.63
E3ME	-	-	-
ALL MODELS	**1.03**	**-0.0054**	0.00***

Table S4: Model differences of the average income elasticity of climate policy costs, and their correlation with GDP per capita. The average elasticity (second column) is computed based on a pooled OLS regression separately for each model including time fixed effects. The slope in the relationship with GDP per capita is estimated based on an OLS regression of the regional elasticity estimate by each model regressed against GDP per capita and shows the marginal change in the elasticity for an increase in GDP per capita by 1,000$ (second column). The third column shows the p-value of significance of a standard one-sided t-test of this coefficient. For E3ME only one country has the required inequality data hance the estimation was not possible.

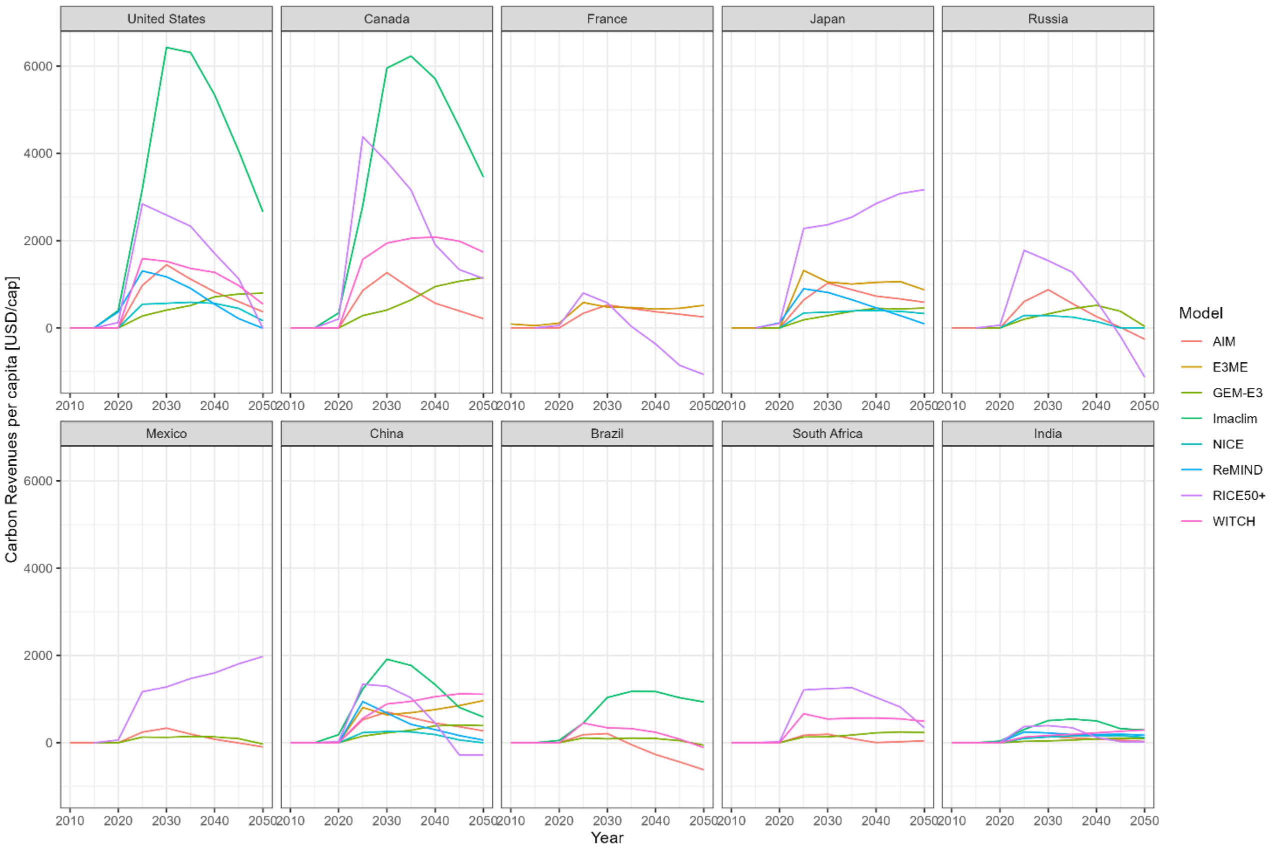

Figure S9: Carbon revenues in the Paris scenario over time (per capita)

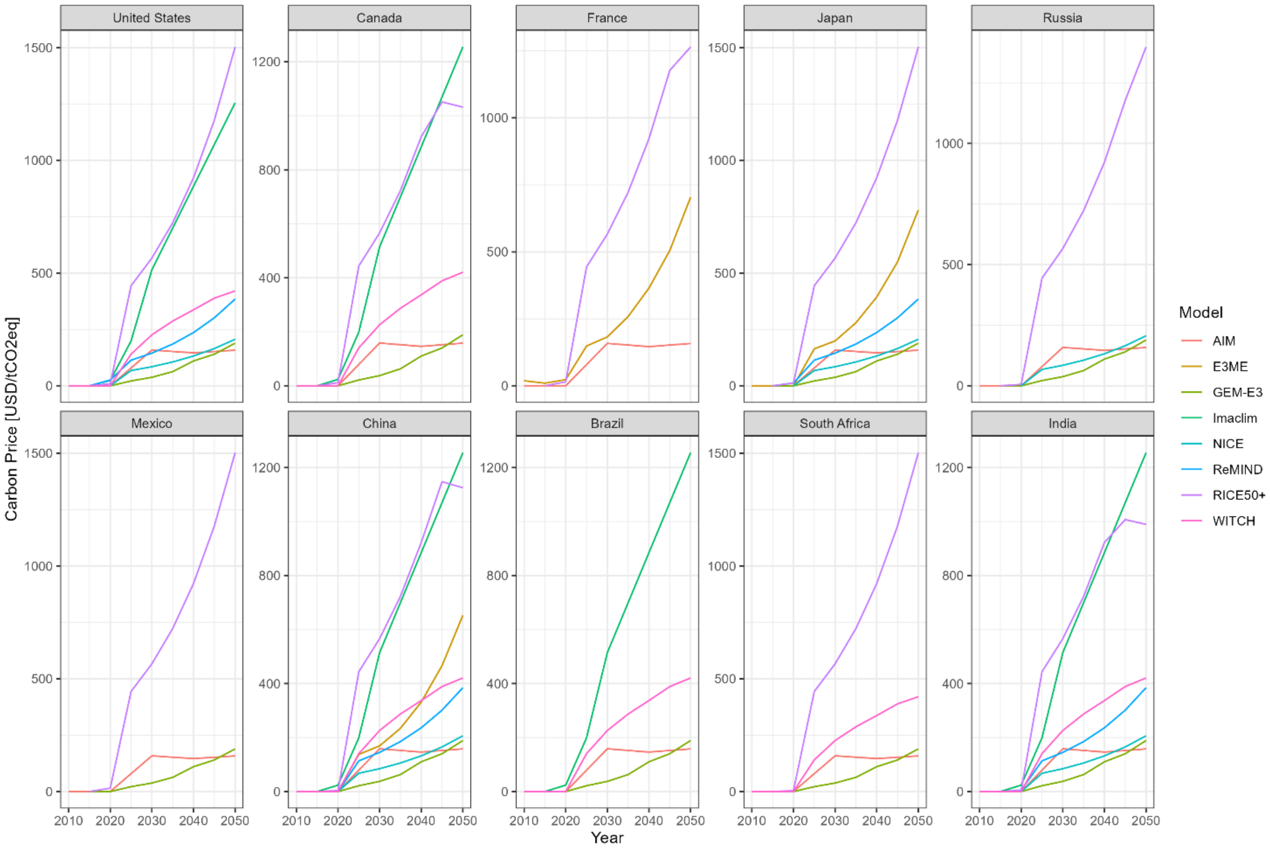

Figure S10: Carbon prices in the Paris scenario over time

	Dependent variable:
	Gini impact [points]
Carbon revenue per capita (1,000)	−0.560*** (0.114)
Canada	0.502 (0.386)
France	−0.233 (0.513)
Japan	−0.439 (0.383)
Russia	−1.591*** (0.391)
Mexico	−1.215*** (0.430)
China	−1.886*** (0.329)
Brazil	−0.946** (0.406)
South Africa	−2.575*** (0.393)
India	−2.442*** (0.342)
E3ME	1.303* (0.744)
GEM-E3	1.330*** (0.288)
Imaclim	−0.955** (0.393)
NICE	1.898*** (0.341)
RICE50+	1.073*** (0.285)
ReMIND	0.343 (0.371)
WITCH	−0.238 (0.344)
Constant	−0.813*** (0.312)
Observations	329
R^2	0.452
Adjusted R^2	0.422
Residual Std. Error	1.572 (df = 311)
F Statistic	15.108*** (df = 17; 311)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table S5: Regression of the Gini impact of equal per capita redistribution on carbon revenue per capita, model and region (Paris to Paris with EPC redistribution scenario). The reference category is the AIM model. Standard errors are given in the parenthesis and significance level is based on a one-sided standard t-test.

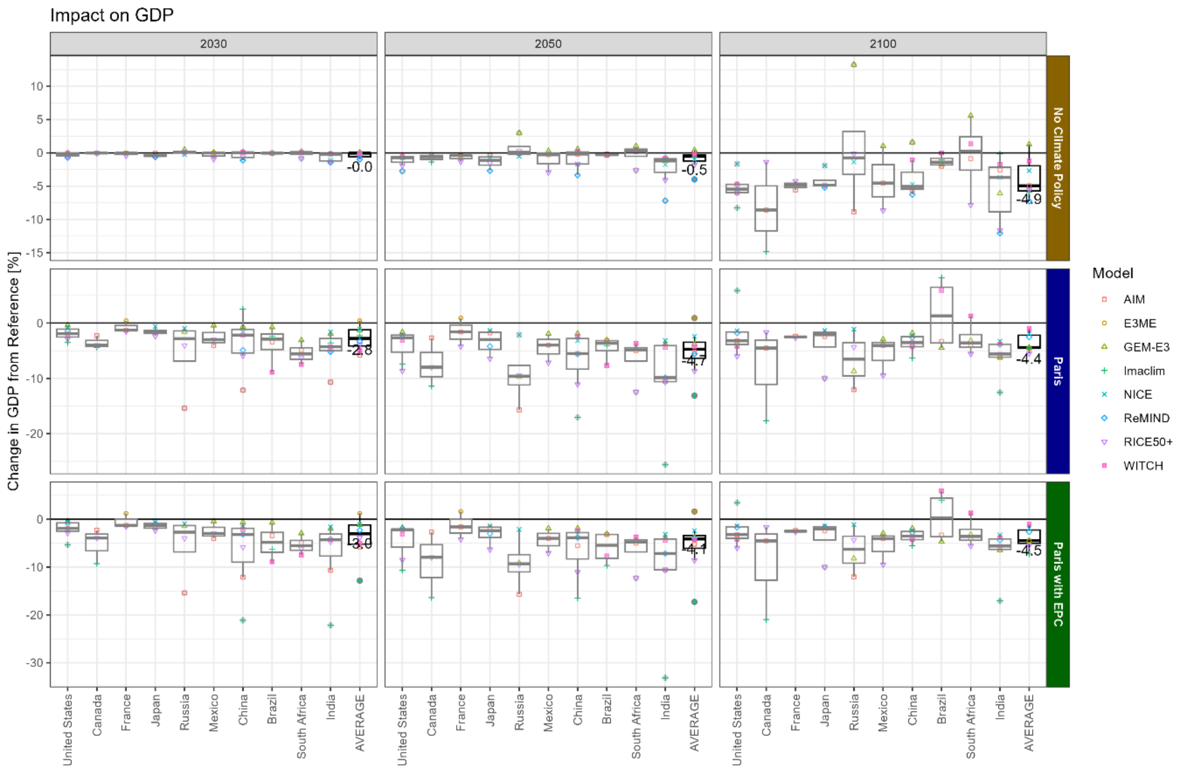

Figure S11: Country-specific Policy Cost in terms of GDP loss from the reference scenario (in %). The top row shows the impact of climate impacts in the Reference scenario, the middle row shows the Paris scenario, and the bottom row includes EPC redistribution. The points show the individual model results, and the boxplot shows the median, inter-quartile range (box), and values within 1.5 times the IQR (whiskers).

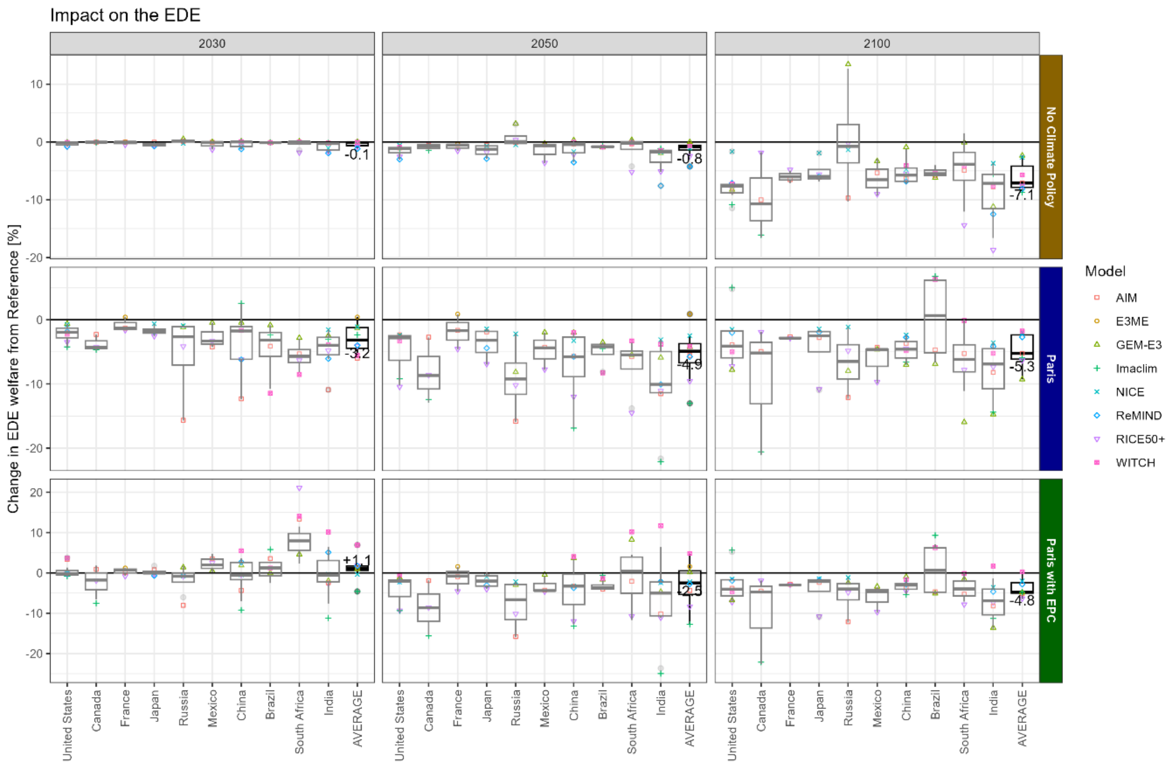

Figure S121: Country-specific welfare impact based on equally-distributed equivalent level of income (EDE) (in %). The top row shows the impact of climate impacts in the Reference scenario, the middle row shows the Paris scenario, and the bottom row includes EPC redistribution. The points show the individual model results, and the boxplot shows the median, inter-quartile range (box), and values within 1.5 times the IQR (whiskers).

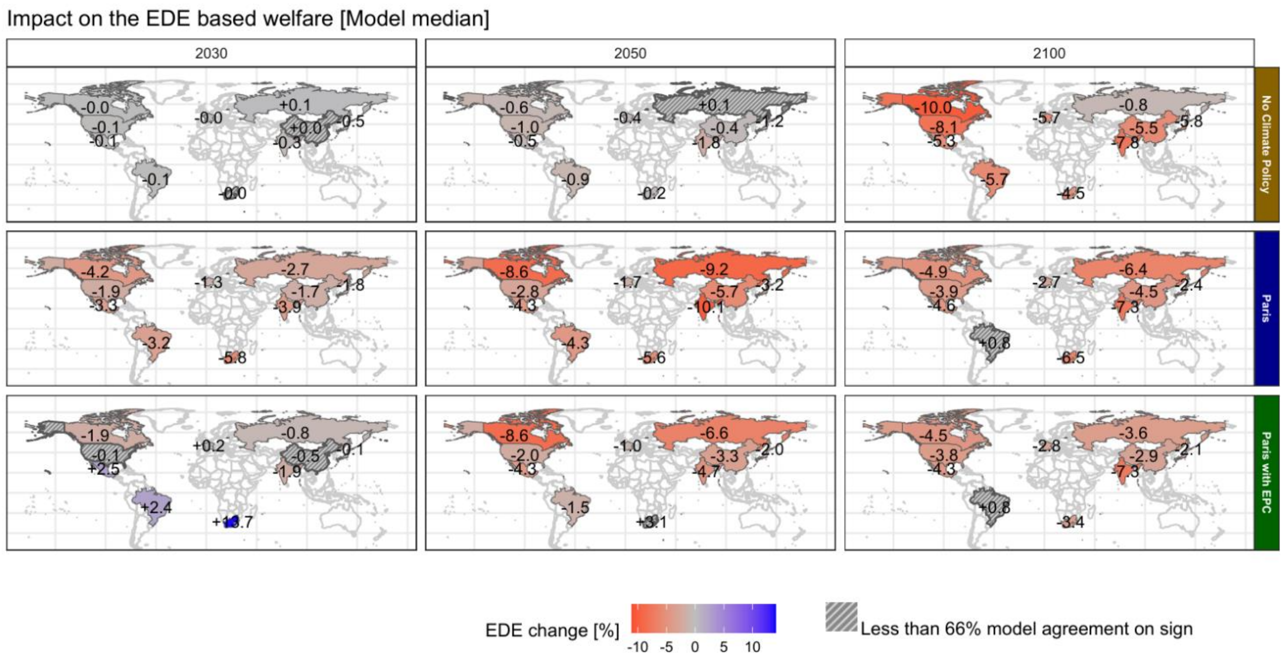

Figure S13: Map of the median across models of the change in the EDE based welfare measure with respect to the Reference scenario without climate impacts (in %). The top row shows the Reference scenario, the middle row shows the Paris scenario without redistribution, the bottom the Paris scenario with impacts and equal per capita redistribution. All scenarios include climate change impacts. Countries with less than two-thirds of model agreement in terms of the sign of the effect are shaded on the maps.

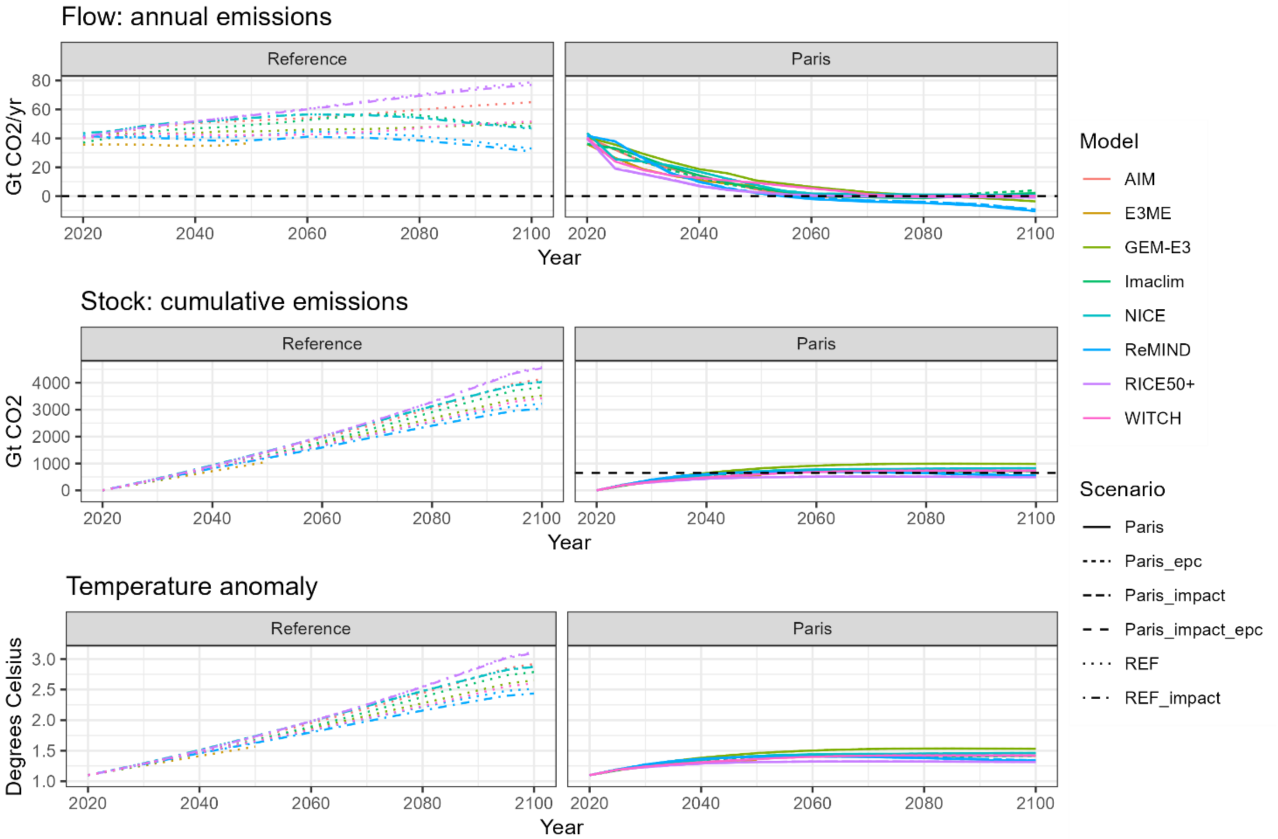

Figure S14: Global emissions and temperature change

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