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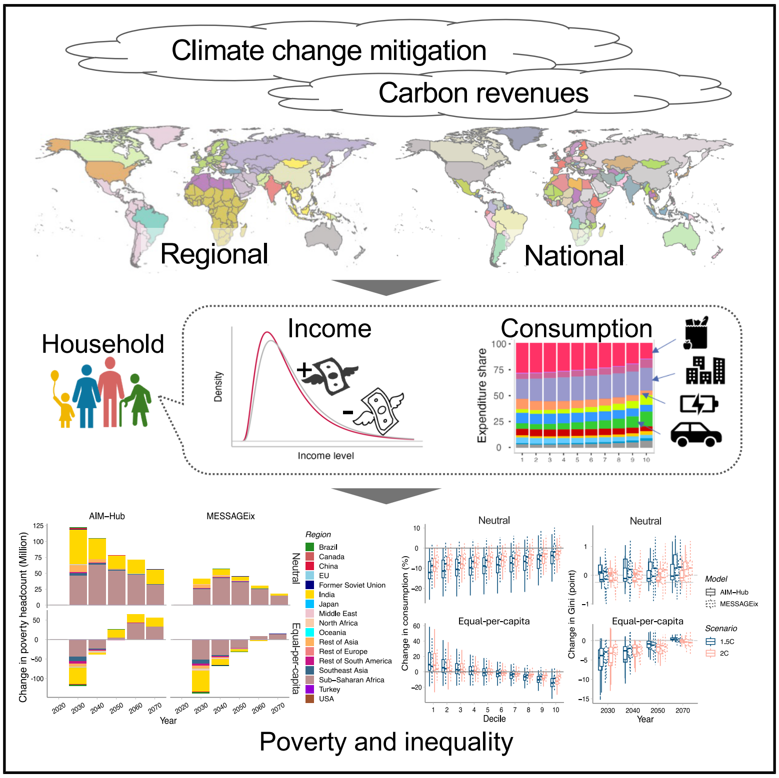
The multi-faceted global poverty and income inequality landscape in a decarbonizing world

Graphical abstract



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In brief

Enhanced climate policies alone may potentially increase poverty and inequality. Understanding these potential consequences and identifying effective countermeasures is essential. This study explores future poverty and inequality across multiple dimensions and evaluates alternative countermeasures, providing insights into future policy integration to support an equitable decarbonization transition.

Highlights

- New indicators are developed for enhanced understanding of climate policy impacts
- Proper carbon revenue redistribution reduces poverty and inequality by mid-century
- Food poverty persists if the increased food price and income loss are not properly addressed
- Energy consumption is more affected in higher-income regions

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The multi-faceted global poverty and income inequality landscape in a decarbonizing world

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SCIENCE FOR SOCIETY Understanding the deep links between climate mitigation targets and the alleviation of income inequality and poverty is necessary to devise strategies that address these challenges in parallel. Evaluations of such strategies in modeling studies conducted at different spatial and temporal scales have shown that, without careful design, stringent climate policies can increase both the poverty headcount and income inequality, especially in India and Sub-Saharan Africa. Addressing social concerns such as income and food poverty and income inequality during the transition toward a low-carbon economy will require well-targeted subsidies and appropriate socioeconomic and technological transitions that help stabilize agricultural and energy service prices and reduce economic losses.

SUMMARY

As nations ratchet up their climate change mitigation goals, associated social concerns regarding poverty and inequality must be considered in policy design and implementation. However, multi-faceted impact assessments of global climate change mitigation embodying regional and sectoral details remain largely deficient. The study focuses on increasing the sectoral resolution of the assessment on climate change mitigation impacts on poverty and income inequality. Countermeasures to alleviate adverse distributional effects are evaluated through two integrated assessment models. The aim is to steer policy formulation toward a sustainable and equitable trajectory for climate change mitigation. Results show that, without careful design, stringent climate policies can increase income and food poverty as well as income inequality, especially in India and Sub-Saharan Africa. Although an equal-per-capita redistribution of domestic carbon revenues offsets adverse distributional impacts, it may not suffice to eradicate poverty or food poverty, especially in many Sub-Saharan African countries.

INTRODUCTION

Climate change has resulted in more frequent extreme weather events such as droughts, floods, heatwaves, and changes in precipitation patterns, all of which have led to major economic losses. These impacts of climate change are also likely to increase poverty,[1] which in itself is a major driver of people's vulnerability to climate-related stresses.[2,3] To protect both current and future generations from the potentially enormous damage caused by climate change, the international community negotiated a joint effort limiting global temperature increase to well below 2°C, including limiting warming to 1.5°C above pre-industrial level levels.[4]

To achieve these temperature goals, carbon neutrality must be achieved within the next few decades. This requires rapid and in-depth transitions from the supply and demand side in the energy sector, changes in land use, urban and rural transformations, as well as lifestyle and dietary shifts.[5] However, scenarios quantifying such global transitions hold limited information when it comes to granular poverty and inequality effects, the analysis

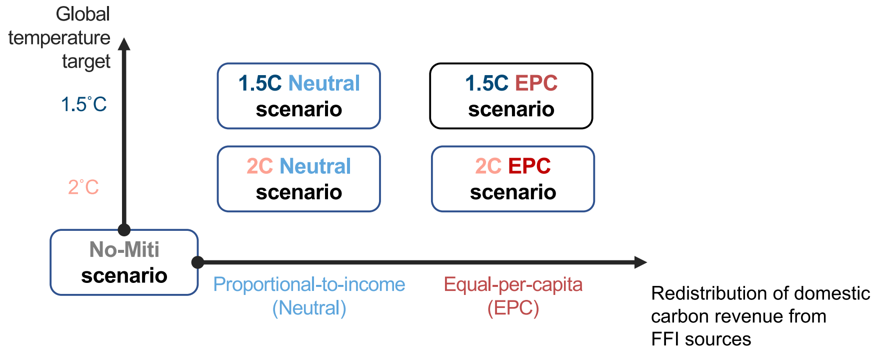

Figure 1. Overview of the main scenarios for analysis

This design applies to both the AIM-Hub and MESSAGEix scenarios. Other scenarios for MPEs and the results of a robustness test can be found in Notes S2 and S4.

of which requires data at high spatial and temporal resolution as well as distributional information within countries. Existing research has shown that the risk of adverse social outcomes associated with climate change mitigation policies, including a worsening of poverty, income inequality, and hunger risk, increases as countries ratchet up their climate change mitigation targets.[6–9] For instance, a transition to carbon neutrality may modestly increase inequality across income classes, with low-income households suffering the worst effects,[10] and between-country income inequalities persisting despite economically optimal climate policies.[11] The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) Working Group (WG) III highlights the importance of understanding the deep links between climate change mitigation and sustainable development goals (SDGs), including poverty eradication and inequality alleviation.[12] Climate and policy scenarios must also consider inequality and poverty to develop climate change mitigation strategies that integrate the multiple policy targets. Studies exploring these issues have shown that the adverse impacts of climate policies on poverty and inequality can potentially be resolved through the redistribution of carbon tax revenues.[13–17]

However, climate change mitigation studies identifying the dynamics of sectoral consumption to understand the poverty and inequality outcomes remain limited. Previous studies have also failed to identify households at risk of falling into poverty. In this study, we addressed the abovementioned gaps by simulating detailed household consumption portfolios and by establishing novel indicators for a multi-faceted assessment. This study aimed to answer the following questions: How does climate change mitigation affect the global poverty and income inequality landscape? Who is likely to be affected? Through what sectors and mechanisms in their consumption basket are households affected? By constructing scenarios in line with the Paris Agreement's long-term temperature targets, our broader objective is to direct attention to future policy integration, i.e., during the IPCC AR7 cycle and by the target year of the 2030 Agenda for Sustainable Development,[18] such that the potential adverse side effects are avoided and the benefits of climate policies are enhanced. Further insights into the effectiveness of countermeasures are obtained by complementing the above analyses with considerations of carbon tax revenue recycling schemes.

We built a no-mitigation (No-Miti) scenario and four mitigation scenarios designed from two dimensions (Figure 1). The first dimension is the global temperature target. We considered global carbon budgets in compliance with the Paris Agreement's 2°C and 1.5°C targets. The second dimension is carbon tax revenue redistribution. Domestic carbon tax revenues from fossil fuel and industry (FFI) sources were recycled to households on a proportional-to-income (neutral) or an equal-per-capita (EPC) basis (Method S4). Climate policy was implemented through a global uniform carbon price. Actual implementation could be very different from this stylized representation; however, it adds value by demonstrating the distinct features, potential effectiveness, issues, and constraints related to the different ambitions of climate policies and recycling schemes. We focused on the direct impact of climate change mitigation and did not consider the benefits of avoiding climate impacts. Scenarios are simulated separately in two integrated assement models (IAMs) to gain insights on scenario robustness and uncertainties. The first is a computable general equilibrium (CGE) model called Asia-Pacific Integrated Model (AIM)-Hub, and the second is a model for energy supply strategy alternatives and their general environmental impacts (MESSAGEix) modeling framework, which centers on an energy system model. Values from AIM-Hub are followed by MESSAGEix values in brackets when presented.

Poverty and inequality assessments are performed in AIM-Poverty, Household, and Income distribution (AIM-PHI) model, where multiple households are considered. It is soft-linked to AIM-Hub and MESSAGEix, which are considered as upstream models, and uses commodity prices and macroeconomic loss from upstream models as input. Poverty is evaluated at the international poverty line of a daily expenditure of \$2.15 per capita (2.15-threshold) if not specified, complemented by higher poverty lines of daily expenditures of \$3.65 and \$6.85 per capita (3.65-threshold and 6.85-threshold) in 2017 purchasing power parity (PPP). Relative poverty is not considered here. National income inequality is measured by the Gini coefficient and consumption loss in population deciles. To determine how the magnitude of distributional effects changes with the stringency of mitigation, marginal policy effects (MPEs) are examined. Detailed household consumption portfolios of 13 commodities under different climate policies were provided for a thorough and multi-sectoral depiction of the distributional impacts of climate change mitigation. This is enabled by a non-linear consumer demand system calibrated to a series of global and national household datasets. Assessments were then extended to poverty risk identification and food poverty at different dietary requirement levels. The income threshold of households at risk of having a daily expenditure level below the

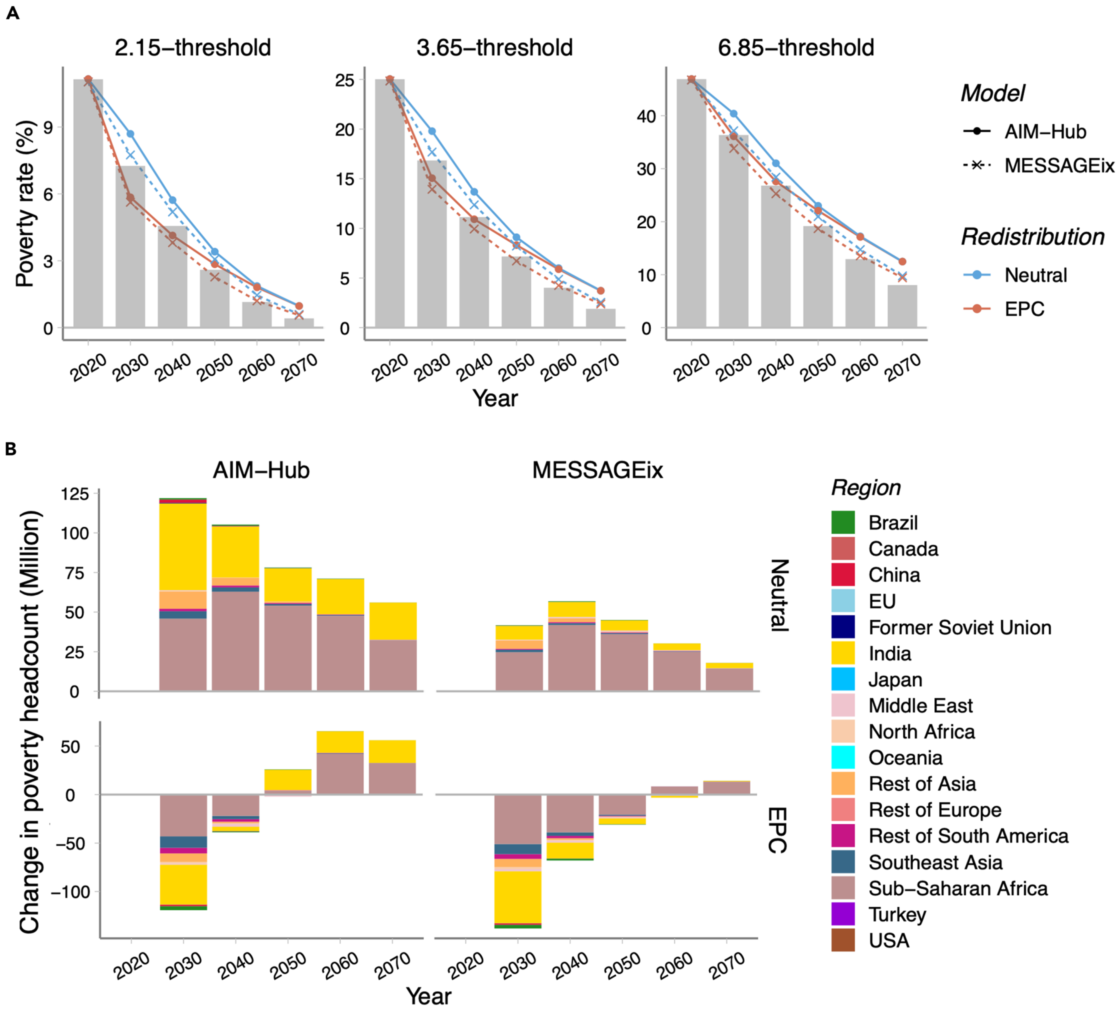

Figure 2. Global poverty projection

(A) Global poverty rate under four different poverty lines. The columns show the poverty rate in the No-Miti scenario. The lines show the poverty rate in the 1.5°C scenario with neutral or EPC redistribution. The 2.15 threshold corresponds to a daily expenditure of $2.15 per capita, which is the international poverty line. The 3.65 threshold and 6.85 threshold correspond to daily expenditures of $3.65 and $6.85 per capita, which are the poverty levels for lower-middle-income and upper-middle-income countries, respectively.

(B) The increase in the poverty headcount measured by the international poverty line in the 1.5°C scenario with different revenue redistribution schemes compared with the No-Miti scenario. According to the No-Miti scenario, the global international poverty rate will decline from 7.2% in 2030 to 2.6% in 2050. In Sub-Saharan Africa and India, 431 and 68 million people will be living with a total daily expenditure below the international poverty line in 2030. The size of the poverty population declines rapidly, regardless of the poverty threshold, due to economic expansion, but it will remain high in Sub-Saharan Africa, where 217 million people will still be living in extreme poverty in 2050.

poverty line under climate policies is identified. It is referred to as the "poverty risk threshold" (PRT) (Figure 3A). The depth of food poverty is investigated because both hunger risk and food security issues are sensitive to significant policy impacts.[8,19]

RESULTS

Poverty headcount and PRT

The global poverty rate increases by 1.4 (0.5) percentage points in the 1.5°C scenario with a neutral redistribution in 2030, meaning that 122 (42) million more people will be living under the international poverty line (Figure 2A). Climate policies have the strongest impact on the poverty headcount in India, Sub-Saharan Africa, and the rest of Asia, resulting in increases in the poverty headcount of 54 (8.7), 46 (25), and 11 (5.3) million, respectively, and accounting for 91% (93%) of the additional poverty headcount (Figure 2B).

EPC redistribution fully offsets climate policy impacts on global or regional poverty, but in 2030, it by no means eliminates absolute poverty, as it decreases the global poverty rate by only 1.4 (1.6) percentage points, leaving 5.8% (5.6%) of the global population still living in poverty. Sub-Saharan Africa would benefit the most, followed by India, with the poverty headcount declining by 43 (51) and 41 (54) million, respectively, in 2030.

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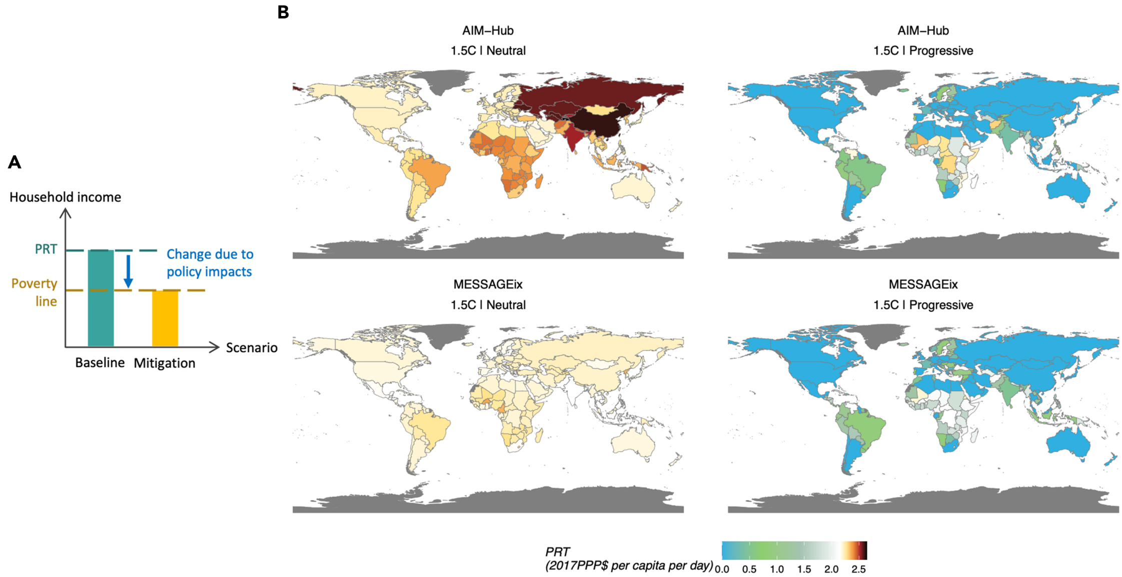

Figure 3. PRTs

(A) Definitions of PRT.

(B) Projections of the PRTs associated with the international poverty line of \$2.15 per capita per day (shown in white) in the 1.5°C scenarios in 2030, in both models and carbon tax revenue recycling schemes.

With a neutral redistribution, climate policies in the 1.5°C scenario result in net consumption losses in most households. In 2030, based on a poverty threshold of \$2.15 per capita per day, the PRT is highest, over \$2.5 per capita per day, in former Soviet Union countries, China, and India (Figure 3B). Among the top 20 countries with the highest PRTs (Table S3), AIM-Hub shows that more than half are former Soviet Union countries, followed by Sub-Saharan African countries. The MESSAGEix scenario showed that 16 of them were Sub-Saharan African countries.

With an EPC redistribution offsetting policy impacts, the PRT declines, but it is still higher than the poverty line in countries with a high poverty headcount or high poverty rate. By contrast, the PRT declines drastically in countries with higher carbon tax revenue per capita, typically in developed countries with high per capita emissions. Both two models show that, among the top 20 countries with the highest PRTs under an EPC redistribution in 2030 (Table S3), 15 (14) are in Sub-Saharan Africa, with the PRT higher than or close to the international poverty line. Former Soviet Union countries no longer stand out due to the considerable amount of carbon tax revenue per capita that households receive (Figure S12). In countries where the PRT is still high or close to the international poverty line, especially Sub-Saharan African countries, an EPC redistribution of domestic carbon tax revenue might not be as effective in elevating consumption levels as expected, a finding that is often masked by the large reduction in the poverty population. While a large proportion of the population could be lifted out of poverty, consumption levels are only slightly improved such that their expenditure levels are likely to again fall below the poverty line due to further policy impacts. PRTs increase in 2050 in both models regardless of the redistribution schemes, indicating the worsening of the impacts from climate policies (Figure S17).

Inequality and changes in household consumption basket

Distributional effects and inequality implications are analyzed by dividing households into ten income deciles, with the 1st decile as the lowest-income group and the 10th decile as the highest-income group domestically. Strong regressive effects occur across income deciles in the 1.5°C scenario with neutral redistribution (Figure 4A). All income groups suffer net consumption loss, with a median level consumption loss of 12.1% (8.7%) in the 1st decile and a 3.7% (1.9%) loss in the 10th decile in 2030 (Figure 4B). An EPC redistribution promotes consumption in the lower-income group, thereby reducing inequality (Figure 4B). In 2030, the 1st decile experiences a substantial gain of 9.7% (8.0%), whereas the 10th decile incurs a substantial net loss of 14.7% (8.5%) in median consumption levels. This substantially reduces the Gini coefficient by 0.34 (0.28) points on the median level globally in 2030.

The consumption basket in different income groups within a country was analyzed to determine how distributional effects were conveyed through household consumption preferences. The two commodities for which net losses in consumption are expected for both the 1st and 10th deciles are "food&beverages" and "energy" (Figure 5A), due to drastic price increases associated with the mitigation scenarios and less elasticity to price changes in lower-income households. To achieve the 1.5°C target, in 2030, out of a total consumption loss for the 1st decile on a global median of 12.1% (8.7%), "food&beverages" accounts for 7.2 (5.5) percentage points and changes in "energy" for 2.6 (3.2) percentage points (Figure 5A). The 10th decile suffers

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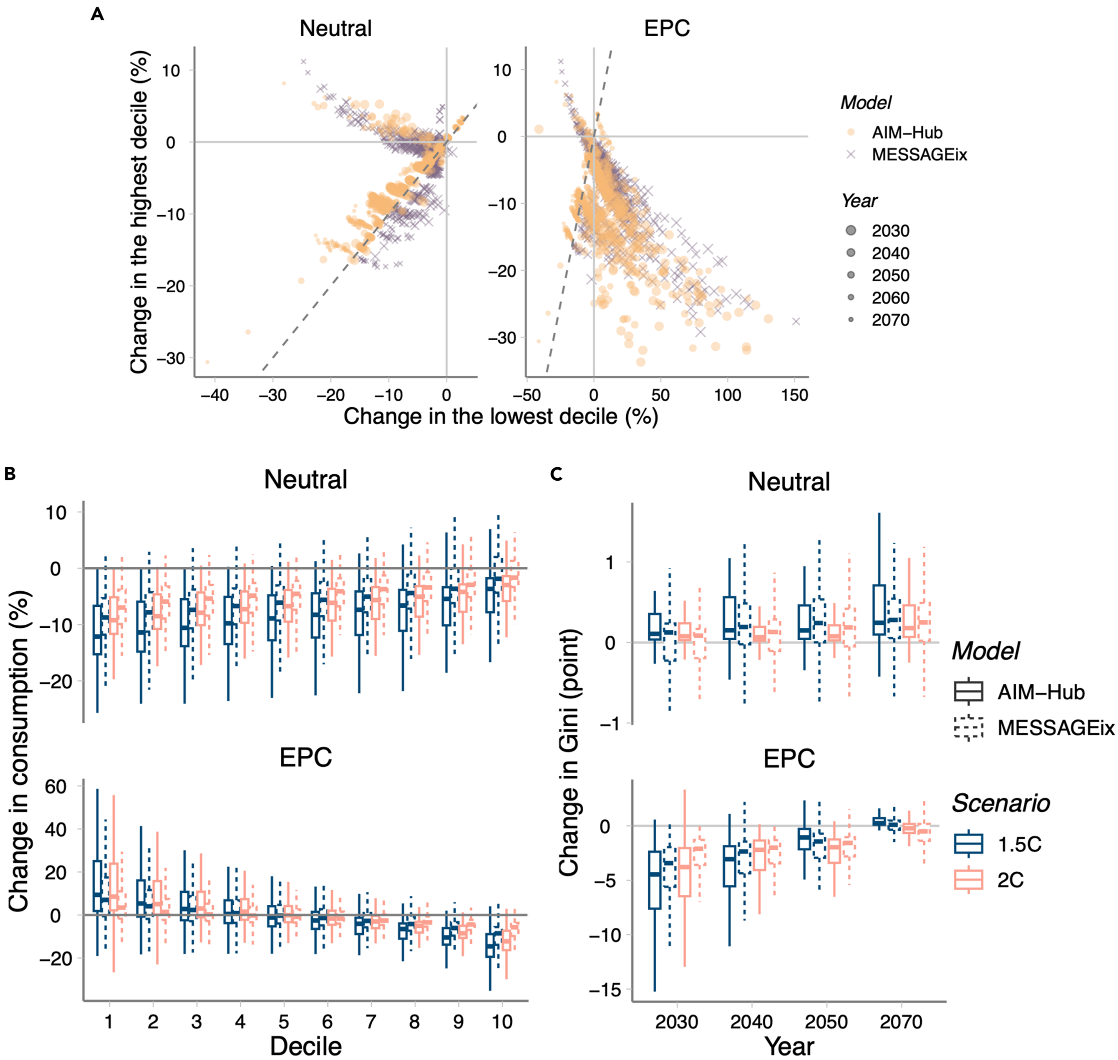

Figure 4. Changes in household consumption and within-country inequality

(A) Changes in consumption in the lowest (1st) and highest (10th) deciles in the 1.5°C scenario. The points above the dashed gray line indicate a regressive effect.

(B) Changes in the total consumption by income decile in 2030. The boxes indicate the range between the lowest and highest quartiles of the change rate of household consumption in each national decile in all modeling regions. The whiskers show the ranges between the lowest (highest) extremes and the lowest (highest) quartiles. The bars in the middle of the box indicate the median consumption change rate. The 1.5°C scenario has larger impacts than the 2°C scenario under both redistribution schemes, but the magnitude of the difference is limited.

(C) Changes in the Gini coefficient in the modeling regions under different mitigation scenarios. Regional output could be found in Note S3. The boxes show the range between the lowest and highest quartiles of the percent change in the Gini coefficient. The whiskers show the ranges between the lowest (highest) extremes and the lowest (highest) quartiles. The bars in the middle of the box show the median percent change in the Gini coefficient.

a total consumption loss of 3.7% (1.9%), with 3.3 (2.9) percentage points coming from "food&beverages" and 1.7 (2.0) percentage points from "energy." Consumption loss declines in 2050, but inequality becomes even greater as commodity prices keep rising.

An EPC redistribution boosts the consumption of all commodities in the 1st decile, most significantly in "food&beverages," "housing&water," "energy," and "transport" (Figure 5B). Although adverse impacts on "food&beverages" and "energy" are partly offset as well, in half of the countries the lowest-income group still faces a net loss in consumption.

Lower-income households in India and Sub-Saharan Africa are the most affected in 1.5°C neutral carbon tax revenue redistribution, with losses in "food&beverages" consumption by the lowest decile of 16.0% (8.1%) and 13.0% (5.2%) in 2030. "Energy" is of greater concern in higher-income countries such as China and Japan as well as for the lower-income populations in the rest of Europe.

MPEs

A significantly positive relationship is observed between the regional additional poverty headcount and the stringency of

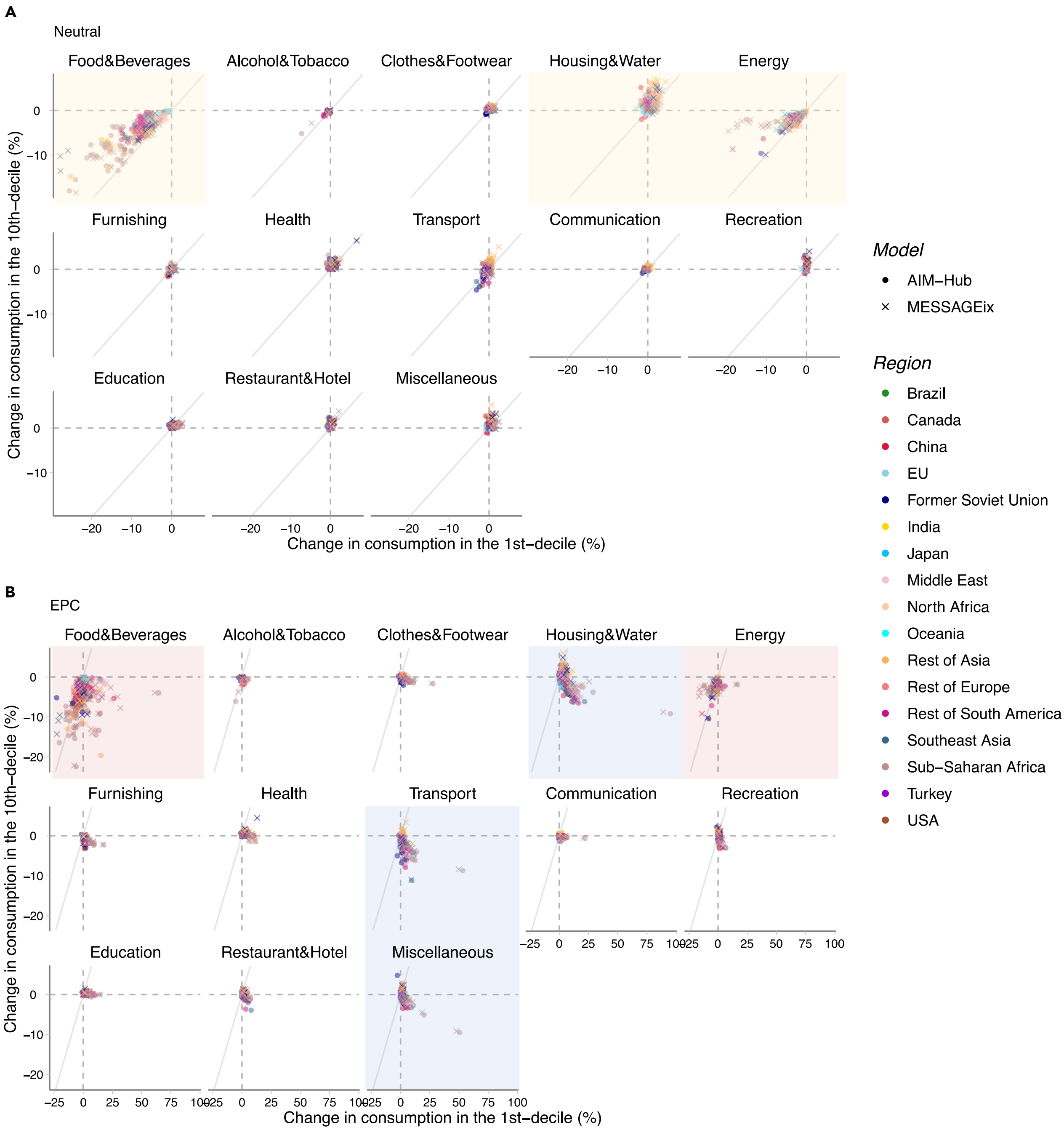

Figure 5. Contributions of commodities and services to the total consumption changes in 2030
(A) Neutral redistribution scenarios.
(B) EPC redistribution scenarios. Dots above (below) the solid gray line indicate exacerbated (reduced) inequality. Dots farther away from the solid gray line indicate stronger regressivity. Yellow shading: consumption losses in the 1st and 10th deciles in the absence of the EPC redistribution; blue shading: significant increases in the consumption level in the 1st decile; red shading: persistent net loss in the 10th decile despite the EPC redistribution.

climate policies. MPEs on the poverty headcount of the CO_2 emission reduction rate (relative to the No-Miti scenario) in 2030 are highest in Sub-Saharan Africa, where a 1% CO_2 reduction results in 1.9 million more people falling below the $2.15 per capita per day expenditure level. MPEs increase with a higher poverty line of $6.85 per capita per day, most prominently in India, China, and Southeast Asia, where there is a large middle- to lower-income population but also a larger policy cost due to the enormous inertia characterizing the transition to decarbonization.

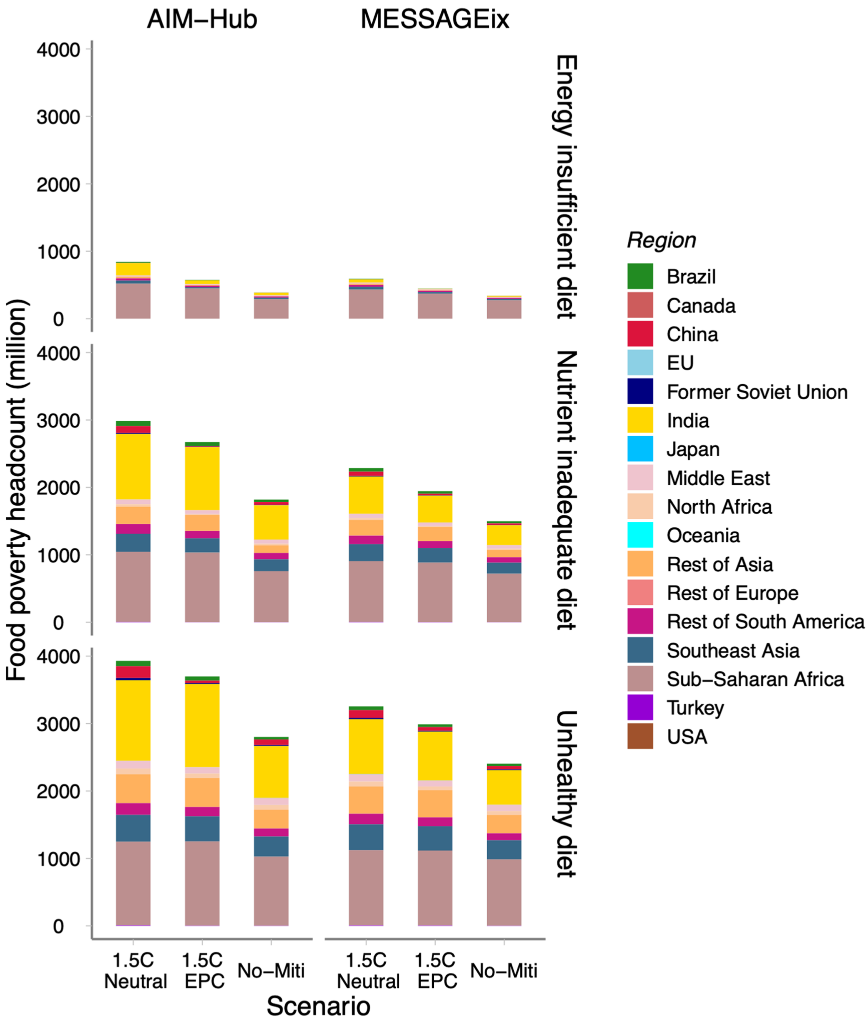

Figure 6. Food poverty projections in 2030

The models project an additional 452 million (250 million) more people unable to afford an energy-sufficient diet, 1,166 million (787 million) more people unable to afford a nutrient-adequate diet, and 1,128 million (849 million) more people unable to afford a healthy diet in 2030 in the neutral redistribution scenario. An EPC redistribution reduces the size of the food poverty population compared with a neutral redistribution, but the benefit is limited.

MPEs on the Gini coefficient are highest in Sub-Saharan Africa, with a 1% reduction in CO_2 emissions reduction leading to an increase in the Gini coefficient by 0.016 points in 2030 (Note S2). Substantial MPEs of 0.012 points in 2030 are also predicted for the rest of Asia. MPEs on the Gini coefficient are greatly diminished across all regions by 2050.

The EPC redistribution reduces the MPEs on the poverty headcount, with a sign reversal in all countries by 2030. In Sub-Saharan Africa, a 1% reduction in CO_2 emissions leads to a 0.56 million decrease in the poverty headcount when accompanied by an EPC redistribution. Huge decreases in the MPEs on the Gini are also predicted, with an increasing carbon price leading to a slight decrease in the Gini by 2030 in most regions. However, the benefit of a progressive redistribution, represented by the EPC redistribution, diminishes over the longer term due to shrinking carbon tax revenues.

Food poverty

Policy impacts on the household consumption of "food&beverages" are deeply relevant to the nutritional aspects of multidimensional poverty. Despite the promising outlook on income poverty alleviation, in all our scenarios food poverty remains a prominent issue, even in 2050. Here, food poverty is measured as people whose total expenditure does not allow them to afford the minimum recommended energy or nutritional intake[20] while maintaining their consumption of other daily necessities. The food poverty lines (FPLs), as shown in Figures S7 and S8, are defined by summing up the following two components. One is the cost indicators representing the minimum food expenditure to meet the dietary requirements, and the second component is the non-food expenditure of the low-income households (Method S5).

The international poverty line is higher than the FPLs for an energy-sufficient diet in most cases and is around the median of the national FPLs for a nutrient-adequate diet in the No-Miti scenario (Figure S7), meaning that it is insufficient for measuring the food poverty defined by nutritional adequacy. FPLs increase in mitigation scenarios due to an increase in food prices, implying a growing difficulty in satisfying the dietary requirements. Although the FPLs continue to increase until 2070, food poverty does not worsen (Figure S10), because a growth in income is also expected.

Food poverty at all levels increases in the 1.5°C neutral redistribution scenario. This effect is most prominent in India, Sub-Saharan Africa, and the rest of Asia (Figure 6). The expansion of food poverty in the mitigation scenarios can be attributed to the rising cost associated with meeting dietary requirements (Method S5) due to rising food prices (Note S1), in combination with a huge loss in household expenditure (Figure 4B). India stands out due to its huge low-income population and the huge consumption loss (15.4% in AIM-Hub and 8.3% in MESSAGEix). A rapid expansion of food poverty due to climate policies in the long term can be expected in the absence of additional socioeconomic changes in food consumption habits and technological changes in the agriculture sector.

The effectiveness of EPC redistribution is highly spatially heterogeneous and differs depending on the level of food poverty

(Figure 6). Notably, in Sub-Saharan Africa, its impact on reducing food poverty is particularly limited because the countries with the large food poverty population, such as Nigeria, also collect a low-carbon tax revenue per capita. For India, which is the country with the largest food poverty population, the reduction of food poverty measured by energy sufficiency is more prominent than nutrient adequacy and a healthy diet because of the huge increases in the FPLs for nutrient adequacy and a healthy diet in the mitigation scenario (Figure S8). Meanwhile, because only part of the revenue is used on food consumption, an EPC redistribution is less effective in reducing food poverty than monetary poverty.

Model intercomparison and the robustness of the policy assessments

The robustness of our insights is assessed by comparing poverty and inequality projections when AIM-PHI is linked to two different upstream models and by evaluating different socioeconomic assumptions across five shared socioeconomic pathways (SSPs).

AIM-Hub projects higher impacts on the poverty headcount due to very large macroeconomic losses, and MESSAGEix generally shows more regressive distributional effects due to drastic price changes (Note S1). MESSAGEix scenarios show smaller macroeconomic losses, especially in Africa, China, and the countries of the former Soviet Union, and much larger price changes in the agricultural sector and energy system, leading to a stronger regressivity of policy costs on household consumption.

The two models differ in PRT projections in the neutral redistribution scenario because AIM-Hub projects significant regional variation in the consumption loss. The consumption loss in the former Soviet Union countries is higher than in Sub-Saharan African countries by more than 7 percentage points. MESSAGEix projects much lower and more evenly distributed consumption loss because it contains fewer details on international trade and sectoral dynamics. However, energy price rises more significantly in Sub-Saharan African countries, leading to the high PRTs. Also, the two models allocate the mitigation effort and resources differently because MESSAGEix is a perfect-foresight model while AIM-Hub is a recursive dynamic model.

When evaluating the robustness against various socioeconomic assumptions, we utilized the Gini coefficient projections for all five SSPs to represent diverse benchmark domestic distributions in both AIM-Hub and MESSAGEix (Note S4). Assumptions for other socioeconomic drivers and energy and food demand are unchanged at their SSP2 default. All cases demonstrate an increase in poverty, income inequality, and food poverty in the 1.5°C neutral redistribution scenario.

The reduction of poverty, inequality, and food poverty due to an EPC basis redistribution is most prominent if the domestic distribution follows the SSP4's assumption but would be less effective following the SSP5's assumption. The variation in the distributional effects between different Gini assumptions is less pronounced than the distinction between the two models. The projections in EPC scenarios are more sensitive to the different assumptions on domestic distribution than the neutral redistribution scenarios. Overall, the temporal trends and qualitative conclusions remain robust.

DISCUSSION

This study makes a meaningful addition to the literature by providing new insights and establishing novel indicators. It examines the global poverty and income (expenditure) inequality landscape from different perspectives but under a stringent carbon budget aimed at achieving the 1.5°C temperature goal in the near-to-medium term. The national-level PRT analysis demonstrates the specific locations and extent to which an EPC redistribution may not suffice. The MPEs by region serve as an easy tool to estimate the poverty and inequality implications of mitigation targets. They are especially useful in lower-income countries where modeling capabilities are yet to be developed. Our study goes beyond an investigation of income poverty by also focusing on detailed consumption loss to show the importance of countermeasures in the key sectors of food, energy, and transport and by constructing food poverty indicators measuring different levels of dietary requirements.

An advantage of our models is that they provide details on the household consumption basket, thus extending our assessment to food poverty at different dietary requirements levels and dissecting the distributional impacts of climate policy into sectoral effects.

The three research questions can be answered as follows. First, how does climate change mitigation affect the global poverty and income inequality landscape? A significantly positive relationship is found between the poverty and inequality indicators and the intensity of climate change mitigation. The EPC redistribution could reverse this relationship, especially in the near term. Food poverty increases significantly regardless of the carbon tax revenue redistribution schemes.

Second, who is likely to be affected? PRTs reveal that low-income households in the former Soviet Union and Sub-Saharan African countries face risks of substantial consumption reduction. Both models agree that the EPC redistribution would not be as effective in reducing poverty as in other regions if only domestic carbon tax revenues were utilized.

Third, through what sectors and mechanisms in their consumption basket are households affected? By determining changes in the household consumption basket, we identify "food&beverages" and "energy" as the sectors where consumption losses were the most difficult to mitigate. This is particularly true for low-income households. This challenge persists due to sharp price increases and the significant proportion of household expenditure allocated to these sectors. Households in India and Sub-Saharan Africa face significant food consumption losses, whereas those in higher-income countries like China, Japan, and parts of Europe see more pronounced energy consumption losses.

Uncertainties surrounding carbon tax revenue are then examined, as the latter is at the center of redistribution policies and greatly affects poverty and income inequality outcomes. Other possible countermeasures and their impacts on poverty and income inequality are considered. The caveats and limitations of our study are then noted, followed by an enumeration of the takeaway messages.

Poverty and income inequality outcomes depend on how carbon tax revenues are recycled. Similar to a previous study,[13] our simulations show that global carbon tax revenues could cover the poverty gap, defined as the deficit of income below the poverty line. However, there are significant disparities in both the magnitude of the domestic carbon tax revenues and the poverty gap at the national level. The largest poverty gap based on the international poverty line is in Sub-Saharan Africa ($151 billion in AIM-Hub and $141 in MESSAGEix in the 1.5°C scenario in 2030), with revenues being 1.29 (1.78) times the amount of the poverty gap. Domestic carbon tax revenue falls short of filling the poverty gap in 2030 in roughly half of Sub-Saharan African countries, while the carbon tax revenues generated in China, the US, and India are substantial and far exceed the domestic poverty gap.

If the coverage of carbon tax revenues is expanded to include all anthropogenic emissions, poverty elimination by 2030 becomes feasible through the targeting of specific populations by progressive redistribution, such as households identified by the PRT. This can be accomplished in most Sub-Saharan African countries even without international transfers. However, there are large uncertainties in the land-use-related emissions reported from inventories and in modeling,[21] both of which add to uncertainties in the carbon tax available for redistribution.

Due to large uncertainties in the emissions pathways and carbon pricing trajectories at the national level, further numerical analysis is not currently possible. Our analysis indicates that a focus solely on a regional level may lead to the overly positive conclusion that carbon tax revenues suffice to achieve poverty eradication, when in fact failure at a national level is likely. This is because a regional assessment often assumes free international financial aid, which is not realistic in many cases.

Under certain stringent climate policy scenarios with equity considerations, carbon prices are set higher in high-income countries and lower in lower-income ones, converging in the long term. This setup reduces mitigation costs and provides more development space for lower-income nations. The carbon tax revenues available for domestic redistribution are uncertain because, while the actual emissions can be higher, the price of emissions is lower for lower-income countries. For example, in Soergel et al.,[14] the carbon price was set according to the development status and converged by 2050. This setting led to higher revenues for redistribution than the loss in total gross domestic product (GDP) by 2040 in Sub-Saharan Africa, India, and other Asian countries, surpassing the GDP loss as indicated in our projections (Figure S13). This suggests a less severe impact of climate change mitigation on poverty compared with the findings of our study.

Concerning the countermeasure, our results suggest that progressive redistribution on an EPC basis encompasses tremendous near-term benefits. However, in its real-world implementation, this very stylized policy representation is subject not only to the uncertainties discussed above but also to institutional and political constraints. Nonetheless, it is considered in the following discussion because it provides useful insights into how national contexts determine the outcomes of carbon pricing.

Effective countermeasures can target the following four aspects: (1) reducing macroeconomic losses, (2) suppressing the increase in the market prices of food and energy commodities and services, (3) creating compensation and subsidies for target groups, and (4) more progressive redistribution of carbon tax revenues and exempting carbon tax for the lower-income population. The final concern has already been discussed in previous studies.[14,22] Examples of other categories include social transformation, such as demand-side management and dietary shifts,[23] and enhanced foreign financial support to compensate for household consumption[14] or investment in green technologies,[24,25] equity consideration in international effort sharing,[26] etc.[22] They can be effective in promoting single or multiple aspects.

Social transformation, characterized by reduced energy demand, dietary changes toward sustainable dietary choices, and enhanced energy efficiency with technological advancements, has the potential to alleviate poverty and reduce inequality by reducing the macroeconomic costs associated with climate change mitigation and by stabilizing commodity prices. Previous studies have suggested such transition strategies have great potential for ending poverty while alleviating environmental pressure.[23] We explored the effectiveness of a socioeconomic-technological transitions package (Note S2) to reduce the adverse impacts of climate policy on poverty and income inequality. It effectively reduces the macroeconomic costs of meeting emission constraints and reduces both the poverty headcount and income inequality significantly in India and Sub-Saharan Africa, irrespective of the poverty line. Unlike the EPC redistribution, the benefits of this policy package on poverty are maintained in 2050 and include a reduction in income inequality, highlighting the potential for leveraging socioeconomic-technological transitions to reduce trade-offs between climate change mitigation and the alleviation of poverty and inequality.

Both the international transfer of carbon tax revenues to compensate for household consumption and enhanced foreign investment are enhanced foreign financial support. Because domestic carbon tax revenues in large Sub-Saharan African countries are insufficient to eradicate poverty or food poverty, a free transfer and redistribution of regional carbon tax revenues to boost household consumption would allow for poverty eradication (Note S1).

Enhanced investment lowers mitigation costs and induces positive employment effects.[25] Foreign investment has been a critical tool in fighting global crises such as climate change. In the World Bank and International Monetary Fund (IMF) Spring Meetings in 2024, the World Bank also announced a commitment to provide 250 million people in Africa with access to electricity before the end of the decade, which requires an estimated $30 billion of public-sector investment and a commitment to undertake regulatory changes.[27] Enhanced foreign direct investment (FDI) has the potential to reduce the macroeconomic loss in mitigation scenarios by boosting the value-added, especially in transportation and service sectors. However, FDI in lower-income countries might harm household consumption before the additional capital formation overtakes the trade deficit. Also, investment in negative emissions technologies (NETs) might decrease the mitigation cost but increase income inequality because the profits might disproportionately benefit private NET company owners.[28] Its effects on poverty and inequality alleviation might be less straightforward than that of foreign financial support that directly compensates for household consumption.

The caveats and limitations in our assessment framework are mainly related to scenario assumptions and the modeling framework.

First, damage from climate change was not considered in our modeling framework. Large uncertainties exist concerning the economic impacts of climate change, mainly reflecting spatial temperature patterns, climate responses, the sectors considered, socioeconomic and policy assumptions, and the estimation and modeling framework.[29–31] While statistical analyses have generally estimated larger economic impacts (percentage loss in GDP),[29,32–34] structural modeling of selected channels results in smaller economic impacts.[30] Rose and coworkers[35] identified clear model-specific tendencies in the climate responses among cost-benefit-analysis IAMs that were primarily influenced by model-specific structural and implementation elements. These uncertainties should be addressed when incorporating damage from climate change into the assessment.

Gilli and coworkers investigated different specifications of the damage function as described in the literature and applied them to within-country income groups to elucidate relationships between climate change and income inequalities.[36] They found an income elasticity of damage of 0.72 under an extension of the damage function by Burke and colleagues.[32] Emmerling and colleagues applied this method in their comparisons of inequality models[37] and found that climate benefits in stringent mitigation scenarios reduce income inequality only in the long term. Inequality continues to grow around mid-century due to the limited climate benefits, even under stringent mitigation scenarios with exhausted carbon revenue recycling. Based on their findings, a worsening of both income inequality and poverty in mid-century can be expected according to our assessment using a similar scenario setup, after accounting for the omission of climate damage in our modeling framework. This again stresses the importance in the coming decades of domestic poverty and inequality countermeasures, more active and targeted international financial support, the scaling up of socioeconomic-technological transitions and demand-side management, as well as equity-based burden sharing.

Second, since the AIM-PHI is an expenditure-based inequality projection tool, it does not differentiate between various household income sources and the resulting heterogeneous responses of household income. Factors such as a policy's impacts on sectoral employment, factor income, and the impacts of climate change on labor productivity could significantly alter income distribution. The literature suggests an enlarged labor demand at different scales and magnitudes due to the energy system transition, albeit with large regional and sectoral differences.[38–40] Climate policies have been shown to relieve only part of the poverty eradication pressure, and the proportional job creation for countries with a large poverty population like India is expected to be generally low.[38] Uncertainties also come from the underlying socioeconomic conditions, where further investigation is needed.

Third, when evaluating the robustness against various socioeconomic assumptions, we only considered the variation of domestic distributions, represented by the Gini coefficient projections, for all five SSPs, while leaving the assumptions for other socioeconomic drivers and for energy and food demand unchanged at their SSP2 default. This is because the full implementation of all five SSPs in both models would be extremely difficult and beyond the scope of this study.

Finally, the scenarios represent the global optimum to achieve utility maximization (AIM-Hub) or cost minimization (MESSAGEix), with both models overlooking local sociopolitical and technological feasibilities or equity-based burden sharing.

In conclusion, lower-income populations in Southeast Asia and the rest of Asia are likely to suffer large losses from climate policies, although the poverty population might not be as large as in India and Sub-Saharan Africa, where food poverty is likely to be exacerbated and is the most persistent.

Income inequality worsens in the absence of progressive redistribution, with the lowest-income decile suffering more net consumption losses than higher-income groups due to increases in the prices of food, energy, and transport services. Lower-income households will suffer from large reductions in food consumption, which in Sub-Saharan African countries will be accompanied by reductions in energy services. Large impacts on energy services for lower-income populations in the countries of the former Soviet Union and in European countries are also predicted. Higher-income households will gain from the transport sector, whereas consumption in this sector will decline in lower-income households. The differences in the policy impacts between 2°C and 1.5°C are small and are distributed unevenly, with greater harm to lower-income countries and households.

Progressive redistribution, such as an EPC redistribution, effectively offsets the adverse impacts of climate policies on poverty and income inequality in the near term but is less powerful over the longer term. Although global carbon tax revenues are sufficient for poverty eradication, domestic carbon revenues are highly uneven across countries, sometimes falling short of the amount needed to fill the poverty gap. Moreover, progressive redistribution of domestic carbon tax revenues is not always effective in elevating consumption levels in Sub-Saharan Africa and the rest of Asia. For both regions, international financial support and well-targeted subsidies are crucial to promoting well-being.

Future research investigating additional policy options and targeting the specific regions, households, and sectors identified in this study would be valuable for integrating a sustainable and equitable climate change mitigation strategy.

METHODS

Overview of the AIM model

Our study took advantage of the AIM framework (Method S1). Consumption and inequality assessment were performed by soft-linking a poverty, household, and income distribution modeling tool (AIM-PHI)[13,41] to a CGE model (AIM-Hub).[42]

AIM-PHI is a top-down consumption distribution and household expenditure modeling tool embodying a log-normal

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assumption and a non-linear demand system. It was first developed to provide quantitative assessments of the future global poverty gap and of the possibility of utilizing carbon tax revenues for poverty eradication.[13] It was then extended to poverty and inequality assessments in the context of national[41] and global[22] climate policy impact assessments using a scenario analysis.

The log-normal distribution captures the national average household consumption in AIM-Hub and matches the Gini projections of the corresponding SSPs.[43] Then, policy impacts beyond income loss and impacts on income distribution are reflected by discretizing this distribution into several income segments and running a numerical consumer demand model with 13 commodities, following the Classification of Individual Consumption According to Purpose (COICOP).[44] In-home energy use is treated separately. The finer discretization at the lower tail of the distribution ensured a better fit for the lower-income population. The demand model "an implicitly directly additive demand system" (AIDADS)[45] is adopted because of its good flexibility and performance with a larger consumption bundle. In AIDADS, household consumption patterns in each country are calibrated to global and national household consumption survey databases. Household consumption and expenditure changes are then projected with respect to a given income and price level under a certain policy shock. With this approach, an analytical income distribution function is derived, allowing a more convenient poverty projection. The AIDADS is based on the linear expenditure system (LES), but it has greater flexibility as it allows for non-linear variations of income elasticity in response to income level.

Carbon tax revenue redistribution is modeled in the AIM-Hub as a lump-sum transfer to the representative household, but the redistribution is then altered in the poverty, household, and income distribution modeling tool (Method S4).

For CGE models like AIM-Hub, we need to choose one good or factor as a numeraire and fix its price as the numeraire to solve the model.[46] In AIM-Hub, CPI is fixed and functions as the numeraire, as in Löfgren et al.,[47] and the model calculates the changes in relative prices. The real price changes are calculated by multiplying the changes in relative prices with the change in the numeraire, which in our model is fixed for the simulation period. The relative prices for emission-intensive goods, e.g., "energy" and "food and beverages," increase significantly in the mitigation scenarios compared with the No-Miti scenario. With a fixed CPI, the relative prices for less emission-intensive goods like transport and services could decrease from the No-Miti scenario.

A multitude of uncertainties arise from scenario assumptions and model selection, significantly impacting poverty projections and assessments of income inequality. Such uncertainties are commonly captured in the model intercomparison literature, in which multiple IAMs with different structures were designed to reflect the same scenario. As a first step toward robustness, in our approach, AIM-PHI was integrated with two global IAMs and followed by a comparison of poverty and inequality projections in compatible 1.5°C and 2°C scenarios. This allowed AIM-PHI-specific biases to be distinguished from the uncertainties embedded in mitigation pathways. AIM-Hub and MESSAGEix can be considered “upstream models” for AIM-PHI.

Overview of MESSAGEix

MESSAGEix is an open-source systems engineering optimization modeling framework encompassing a macroeconomic model (MACRO), a partial equilibrium land-use sector simulation Global Biosphere Model (GLOBIOM), and a Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE), which is a partial equilibrium energy system model[48,49] that has been widely used for mid-to-long-term energy system planning, policy assessment, and scenario development.

Rather than the full MESSAGE-MACRO-GLOBIOM linkage, in this study, climate policy scenarios are drawn from energy system modeling with MESSAGE, with a simplified macroeconomic balance obtained using MACRO and land-use allocation using a land-use emulator. MESSAGE is a linear programming energy system model with global coverage that, for numerous energy conversion technologies, takes into account the interdependencies of energy systems and resource extraction, the processes of conversion, transportation, and distribution, and import and export, as well as final utilization.

The open-source MESSAGEix framework[50] contains a land-use emulator with a large variation of pre-existing scenarios. A composite of those scenarios is determined by weighting factors to meet agricultural demand. As the changes in land rent and wage are not simulated in the GLOBIOM model, the main driver behind the price fluctuation in the agriculture sector is land productivity, which leads to a decrease in the annual agricultural price if there is no other interference.

By placing constraints on greenhouse gas emissions, investments, and technology adoption, the model estimates the least-cost portfolio of mitigation technologies, yielding technology-specific sectoral responses, for example, price indexes and the consumption of energy carriers at different levels, the demand and production of different industries, the capacities of the power sector (among other land-use sectors, especially the agricultural sector), output, and macroeconomic indicators.

Scenarios

In this paper, a No-Miti scenario and four mitigation scenarios, with global carbon budgets in compliance with the Paris Agreement's 2°C and 1.5°C targets, based on socioeconomic narratives, population, and GDP projections for SSP2 (released in 2018), were considered as the main scenarios for analysis (Method S2). The poverty projections in the No-Miti scenarios for both models were harmonized to follow the SSP2 baseline projection. The temporal scope of our simulation spans the years 2020 to 2100; however, the analytical focus ends in 2070 to maintain relevance to considerations of poverty and carbon tax revenues, the significance of which diminishes over extended temporal horizons, and to avoid enlarged long-term uncertainties in the socioeconomic pathways, consumer preference shifts, and policy packages.

Carbon tax revenues are distributed back to households in proportion to income as the default, with an alternative option of an EPC distribution. Note that our model assumes a global uniform carbon price and does not generate carbon tax revenues for redistribution to households after net-zero CO_2 emissions are reached. This simple scenario is chosen for its easy implementation in models with different paradigms. Carbon tax revenues from CO_2 emissions from all FFI sources are distributed back to households within the country either on a neutral (proportional-to-income) or an EPC basis. As no international transfer is considered, regional emissions given by AIM-Hub are downscaled to national emissions, referring to a previous methodology[51] with adaptations for implementation in AIM-PHI (Method S3).

Assessment indicators

Poverty simulations are based on three poverty lines, with a focus on the extreme poverty line of a daily expenditure level of $2.15 per capita. PRTs can be understood as the income threshold of households whose daily expenditure levels would fall below the poverty line due to climate policies. For example, at a poverty line of $2.15 per capita per day, the PRT equals the baseline income of households with a daily expenditure of $2.15 per capita per day in the mitigation scenario. Dividing the PRT by the corresponding poverty line yields a "poverty risk index" (PRI). The closer the PRI is to 1, the less sensitive the country in question is to the policy shock, whether positively (PRI < 1) or negatively (PRI > 1). PRT was evaluated here because it directly shows the income thresholds of households at risk of falling into poverty and the extent of the impacts on the consumption of lower-income households.

MPEs on poverty and income inequality are analyzed in accordance with the concept of marginal SDG emissions values, as defined by Fujimori and colleagues.[52] A set of counterfactual scenarios was run in which the remaining global emissions budget ranged from 500 to 1,400 Gt CO_2 at increments of 100 Gt CO_2. The responses of the poverty headcount and inequality index to the stringency of climate policies were then analyzed by running linear regressions. The CO_2 reduction rate relative to the No-Miti scenario served as the proxy for climate policy stringency. The 1.5°C and 2°C scenarios described in the main body of this paper also fall into this scenario dataset.

Food poverty is measured as the populations unable to afford the cost of an energy-sufficient diet, a nutrient-adequate diet, or a healthy diet[53] while maintaining their consumption of other daily necessities. The cost indicators for different dietary requirements differ across countries and are scaled by national food price projections to derive the future cost thresholds in AIM-PHI (Method S5). A detailed portfolio of household consumption loss of different commodities, including in-home energy services, transport, and health, is expressed in income deciles to reveal the key sectors and populations at which countermeasures should be targeted.

RESOURCE AVAILABILITY

Lead contact

Requests for further information should be directed to and will be fulfilled by the lead contact, Shiya Zhao (zhao.shiya.j46@kyoto-u.jp).

Materials availability

This study did not generate new unique materials.

Data and code availability

The scenario data and codes used for scenario analysis are available in Zenodo (https://doi.org/10.5281/zenodo.11517815).

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AUTHOR CONTRIBUTIONS

Conceptualization, S.Z., S.F., J.M., and J.S.K.; methodology, S.Z., S.F., J.M., and J.S.K.; software, S.Z., S.F., and K.O.; investigation, S.Z.; visualization, S.Z.; writing – original draft, S.Z.; writing – discussions and review and editing, S.Z., S.F., J.M., J.S.K., K.O., T.H., and S.S.V.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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Supplemental information

The multi-faceted global poverty and income inequality landscape in a decarbonizing world

Shiya Zhao, Shinichiro Fujimori, Jihoon Min, Jarmo S. Kikstra, Tomoko Hasegawa, Ken Oshiro, and Saritha Sudharmma Vishwanathan

Supplementary information

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Supplemental Methods

Method S1 Modeling framework

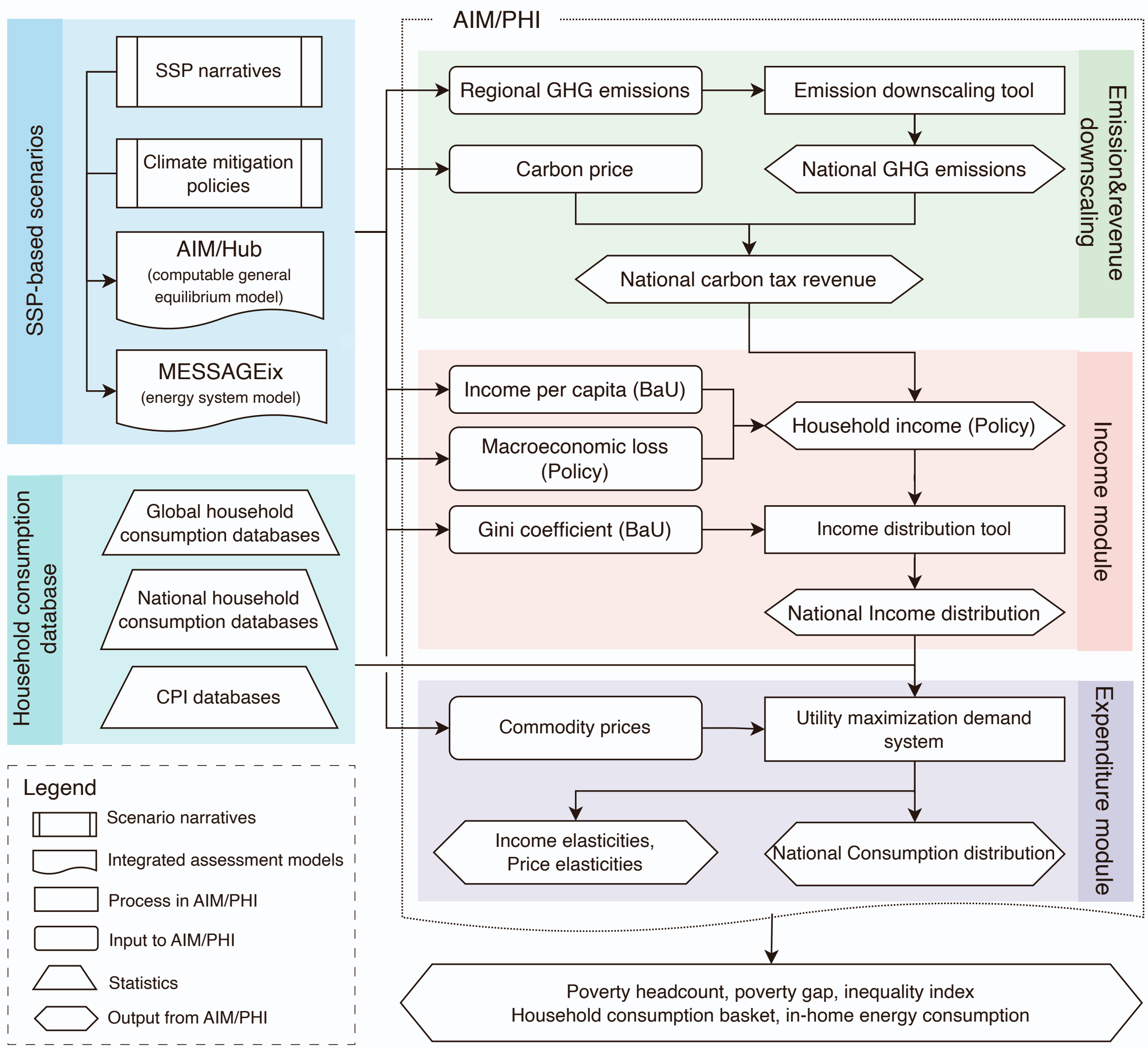

Figure S1 Modeling framework.

Climate mitigation scenarios are simulated in AIM-Hub with 17 modeling regions based on socioeconomic assumptions and climate policies, namely SSP2 narratives and global carbon budgets designated in our study. These scenarios provide the factors affecting household consumption and, consequently, poverty and income inequality. The factors identified in our study include macroeconomic income loss, price changes in commodities, national income per capita, and other demographic features. The models providing this information to AIM-PHI are referred to as "upstream models". This information is then applied by the AIM-PHI model to processes at national and household levels.

The AIM-PHI model primarily consists of an income module and an expenditure module, built on a variety of global and national datasets. Details on the AIM-PHI model and its linkage to AIM-Hub can be found in previous studies [1,2]. In this study, emissions downscaling and carbon tax revenue recycling modules were added (Figure S1) and are explained later. The World Bank recently updated the poverty lines to daily expenditures of \$2.15, \$3.65, and \$6.85 per capita in 2017 PPPs. The model coincides well with historical data at the national level (Figure S2), although the global poverty rate in 2020 was significantly higher (11.1%) compared to the WDI statistics (9.7%). This difference can be attributed to the underestimation of the global poverty rate due to missing national statistics and the imputation method used by the WDI.

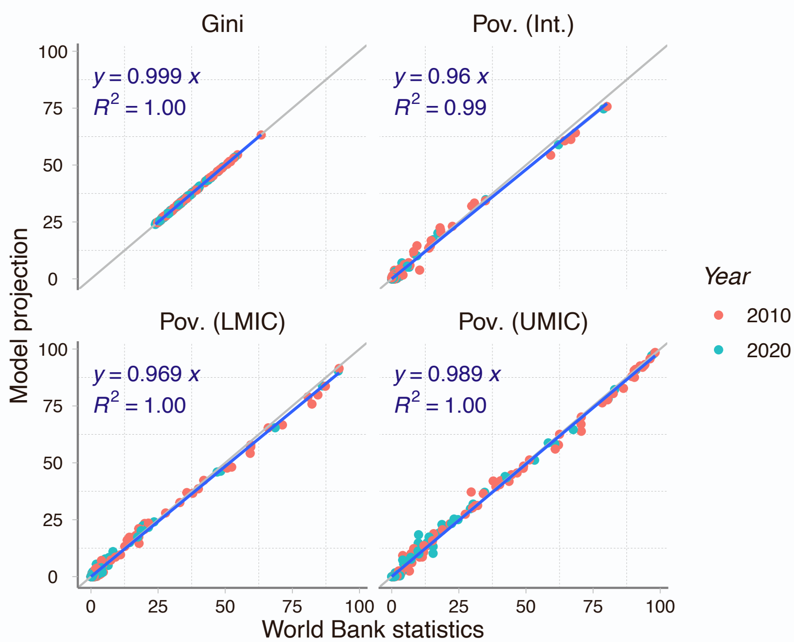

Figure S2 Comparison between model projections and World Bank statistics. The grey solid line is the y = x line and the blue line is the fitted line between x (World Bank statistics) and y (Model projection). The unit for poverty rate (Pov.) is percentage (%) and the unit for Gini is point.

To gain insights into model-specific tendencies and the uncertainties in the mitigation pathways, MESSAGEix was included as an upstream model. MESSAGEix is a versatile, dynamic systems-optimization modeling framework featured by the Model for Energy Supply Systems And their General

Environmental impact (MESSAGE), a linear/mixed integer optimization model that minimizes the system cost for a given energy service demand. Details regarding this model can be found in the paper of Huppmann and coworkers[3]. MESSAGEix provides prices only in the agriculture sector and for energy carriers in 12 modeling regions, which are downscaled in AIM-PHI. The price trajectories of other commodities are kept the same as those from compatible scenarios in AIM-Hub, thus inherently introducing biases and inconsistent issues.

Method S2 Scenarios

Table S1 Scenario setup in the two upstream models

Scenario		**No-Miti**	**2°C Neutral**	**2°C EPC**	**1.5°C Neutral**	**1.5°C EPC**
Socioeconomic assumptions	GDP and demographic projections	National projections from SSP2 narratives				
	Time horizon	2020-2100				
Climate policies and climate change	Carbon budget	-	1000Gt GHG emissions		500Gt GHG emissions	
	Carbon price	-	Global uniform carbon price			
	Climate change impacts	-				
Poverty and inequality related countermeasures	Carbon revenue recycling	-	Proportional to income	Equal per capita	Proportional to income	Equal per capita

Figure S3 Macroeconomic indicators in the two upstream models. a) Carbon price trajectories. b) GDP loss rate.

Table S2 Modeling regions and regional aggregates

Regional aggregate	AIM-Hub Region code	AIM-Hub Region	MESSAGEix Region code	MESSAGEix Region
Africa and Middle East	XNF	North Africa	AFR	Sub-Saharan Africa
	XAF	Sub-Saharan Africa	MEA	Middle East and North Africa
	XME	Middle East		
China	CHN	China	CHN	China
Rest of Asia	IND	India	SAS	South Asia
	XSE	Southeast Asia	RCPA	Centrally Planned Asia
	XSA	Rest of Asia	PAS	Other Pacific Asia
Europe	XE25	EU25	WEU	Western Europe
	TUR	Turkey		
	XER	Rest of Europe	EEU	Central and Eastern Europe
Former Soviet Union	CIS	Former Soviet Union	FSU	Former Soviet Union
Latin America	BRA	Brazil	LAM	Latin America and The Caribbean
	XLM	Rest of South America		
North America	CAN	Canada	NAM	North America
	USA	United States		
PAO	XOC	Oceania	PAO	Pacific OECD
	JPN	Japan		

Method S3 Emissions downscaling

Similar to Fujimori and colleagues' work[4], national fossil-fuel and industrial (FFI) CO_2 emissions are described by a convergence factor, defined by emissions intensity, and an inertia factor, defined by the emissions in the previous year, as shown in Eq. 1:

$$\mathrm{EM}_{r,t} = \alpha_t \times \mathrm{EI}_{r,t} \times \mathrm{GDP}_{r,t} + (1 - \alpha_t) \times \mathrm{EM}_{r,t-1}, \qquad \text{Eq. 1.}$$

where $\mathrm{EM}_{r,t}$ is the FFI CO_2 emissions in country r and year t; $\mathrm{EI}_{r,t}$ is the FFI CO_2 emissions intensity (CO_2 emissions per unit GDP) in country r and year t; $\mathrm{GDP}_{r,t}$ is the GDP in country r and year t and is the driving force; and α_t and $(1 - \alpha_t)$ are the weighting coefficients between the convergence ($\mathrm{EI}_{r,t} \times \mathrm{GDP}_{r,t}$) and inertia ($\mathrm{EM}_{r,t-1}$) factors.

CO_2 emissions intensity $\mathrm{EI\_CO2}_{r,t}$ is then described by Eq. 2, using 1) the country-specific benchmark emissions intensity (EI_{r,t_0}), calculated from the Edgar database associated with the regional average emissions intensity change ratio $\left(\frac{\mathrm{EIA}_{region,t}}{\mathrm{EIA}_{region,t_0}}\right)$, and 2) the regional average emissions intensity:

$$\mathrm{EI}_{r,t} = \beta_t \times \mathrm{EI}_{r,t_0} \times \left(\frac{\mathrm{EIA}_{region,t}}{\mathrm{EIA}_{region,t_0}}\right) + (1 - \beta_t) \times \mathrm{EIA}_{region,t}, \qquad \text{Eq. 2.}$$

where $\mathrm{EIA}_{region,t}$ is the regional average FFI CO_2 emission intensity in year t and β_t and $(1 - \beta_t)$ are parameters representing the inertia and convergence in the emissions intensity (national emissions intensity equals regional average emissions intensity when $\beta_t = 0$.) For negative emissions, Eq. 2 can be revised into a linear function indexed by β_t, which is linearly interpolated between the current record and the regional average emissions intensity.

Finally, national FFI CO2 emissions from Eq.1 ($\mathrm{EM}_{r,t}$) are upscaled to match the regional outputs from AIM-Hub using Eq. 3:

$$\mathrm{EM}^*_{r,t} = \mathrm{EM}_{region,t} \times \frac{\mathrm{EM}_{r,t}}{\sum_r \mathrm{EM}_{r,t}}, \qquad \text{Eq. 3.}$$

where $\mathrm{EM}^*_{r,t}$ is the national CO_2 emissions in country r and year t and $\mathrm{EM}_{region,t}$ is the regional CO2 emissions given by AIM-Hub. Values are assigned to the weighting factors α_t and β_t according to Eq. 4 and Eq. 5 so that full convergence is achieved in 2100.

$$\alpha_t = i \times \frac{1}{n-1}, \qquad \text{Eq. 4.}$$

$$\beta_t = 1 - i \times \frac{1}{n-1}, \qquad \text{Eq. 5.}$$

where $t \in [0, n]$, $t_0 = 2005$ is the benchmark year and $t_n = 2100$ is the year of full convergence.

Maps of the national FFI CO_2 emissions after downscaling can be found in Figure S4 and Figure S5.

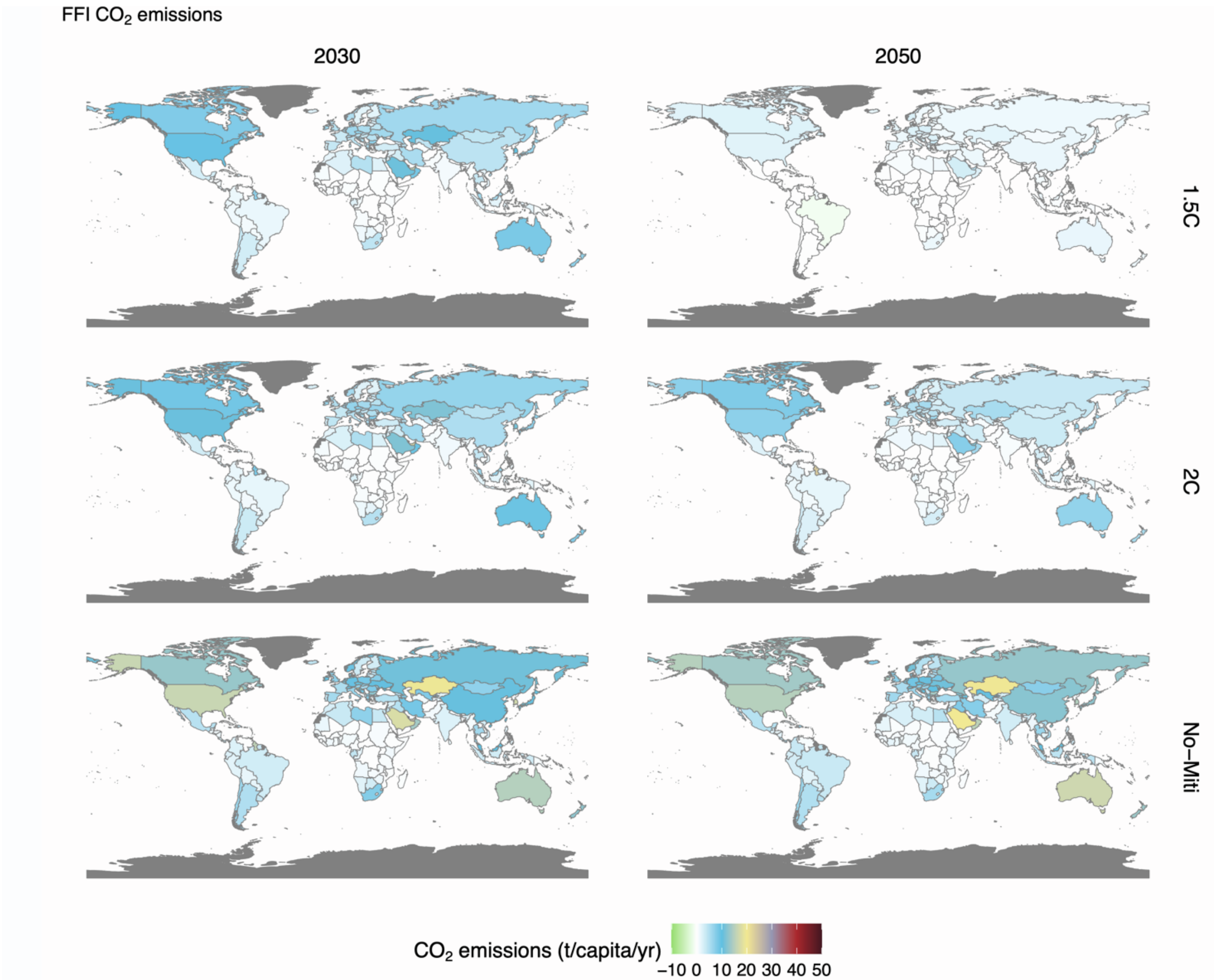

Figure S4 FFI emissions in AIM-Hub scenarios after downscaling.

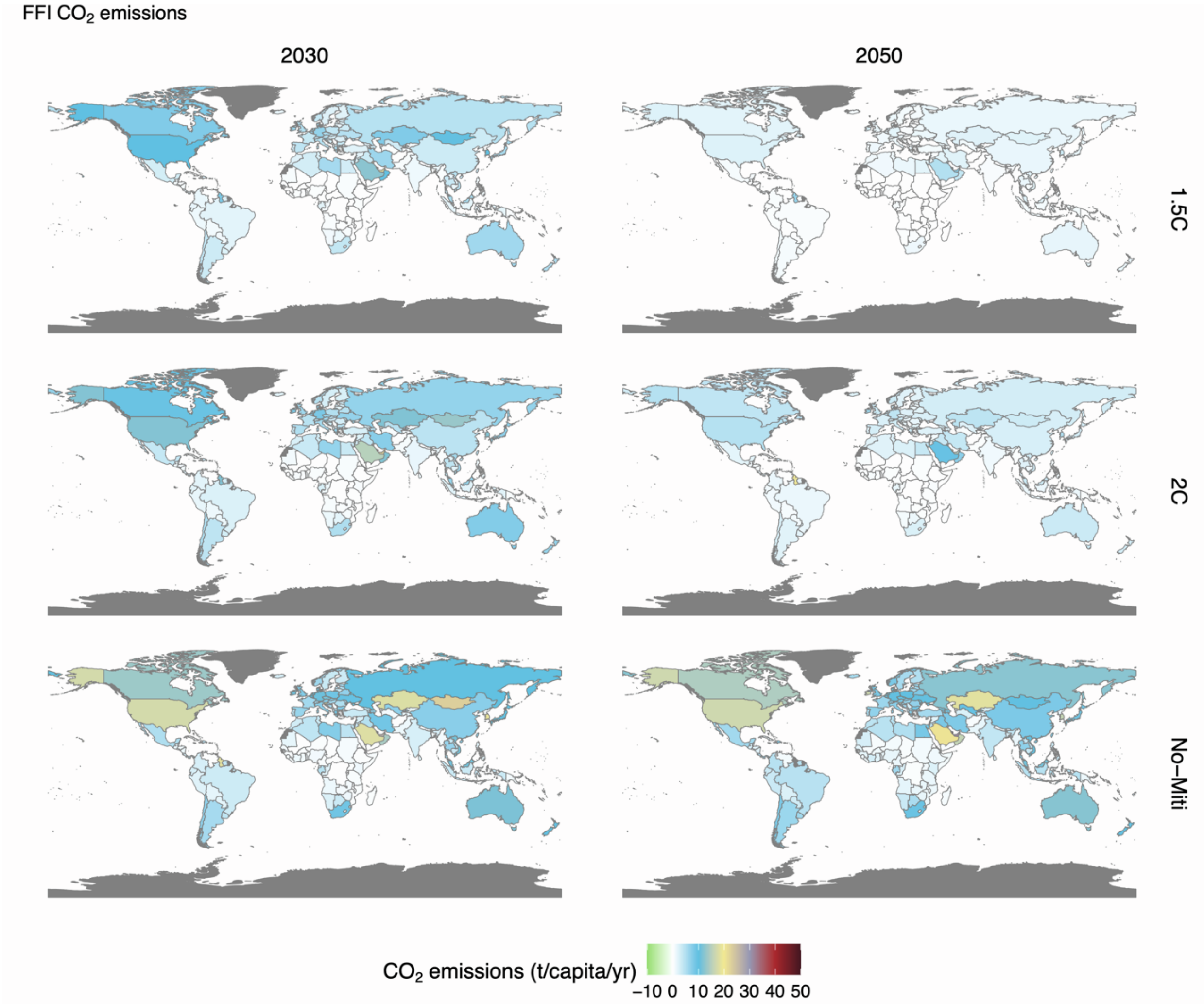

Figure S5 FFI CO2 emissions in MESSAGEix scenarios after downscaling.

Method S4 Implementation of carbon revenue redistribution

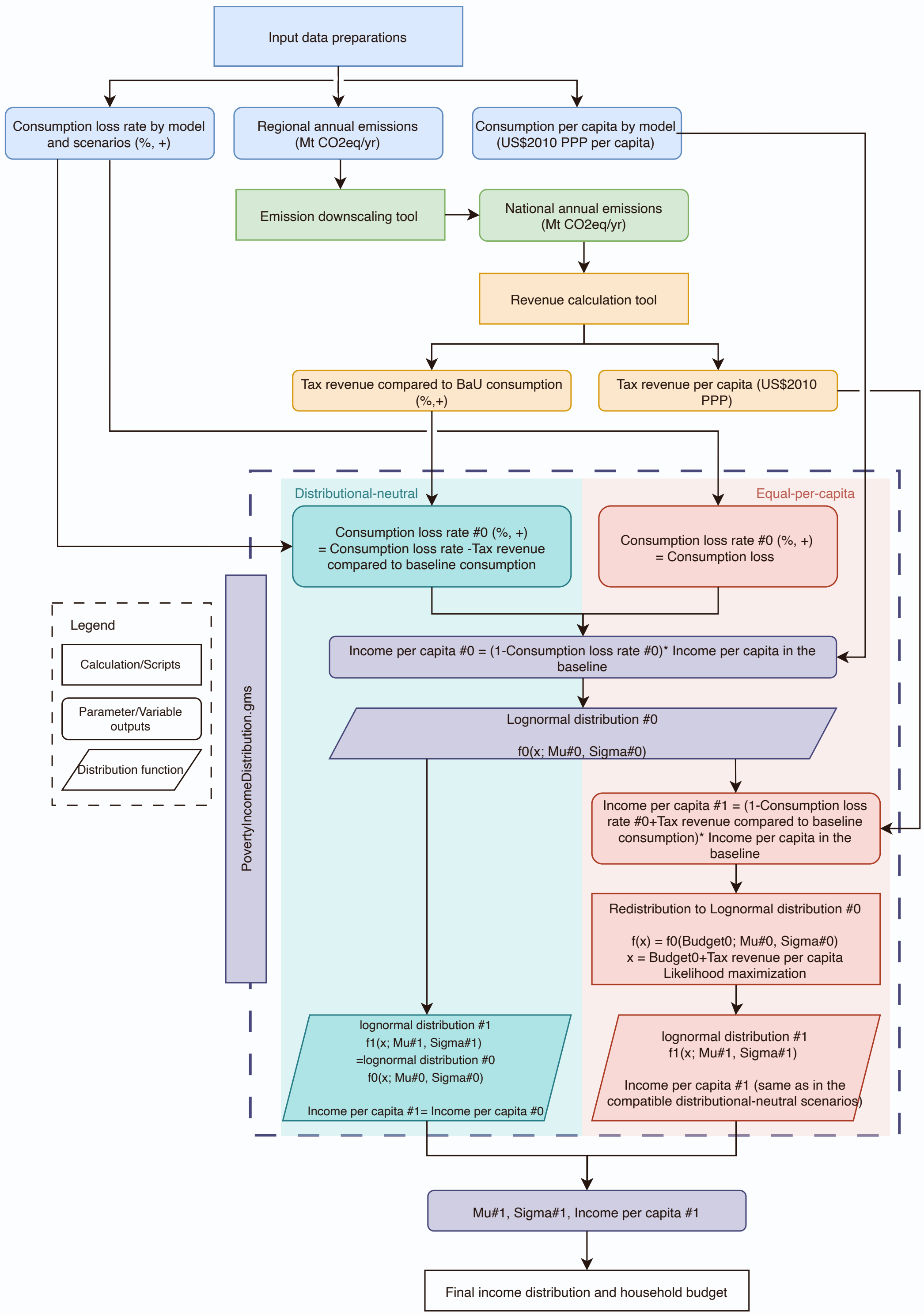

Figure S6 Implementation of different carbon tax revenue recycling schemes in AIM-PHI.

In AIM-Hub, carbon tax revenue is recycled to a representative household as a lump-sum transfer that increases household income and consumption, but the distribution is then altered in AIM-PHI to be either neutral or equal-per-capita. MESSAGEix doesn't assume a representative household but has a similar underlying assumption of a lump-sum transfer by compensating the system cost with carbon tax revenue. In the neutral redistribution scenario, all households in AIM-PHI have the same change ratio in their total expenditures as in the representative household, meaning that tax revenues are allocated on a proportional-to-income basis. In the EPC redistribution scenario, carbon tax revenues are removed from household consumption in the representative household as provided by the neutral redistribution scenario; instead, households are compensated individually on an equal-per-capita basis, as illustrated in Figure S6.

Method S5 Food poverty assessment

Food poverty is defined differently across countries and agencies[5–7], but a common feature is an attempt to depict the status in which people fail to obtain food that provides enough energy and nutrition, whether due to low income, limited access to healthy food, or poor cooking devices and skills. It is often measured as people who cannot afford a food basket providing the minimum recommended energy or nutritional intake[6]. The income threshold to afford the cost of this basket, while considering other household consumptions, is referred to as the food poverty line (FPL). The Food Prices for Nutrition DataHub[8] provides global statistics on the 33 indicators of the cost and affordability of healthy diets and related topics, by combining food item availability and prices from the International Comparison Program (ICP)[9] with food composition and nutritional requirements data from various sources. We adopted the cost indicators as the FPL at three levels: the average daily cost of an energy sufficient diet that meets caloric adequacy for daily subsistence; the average daily cost of a nutrient adequate diet that avoids nutrient deficiency or excess; and the average daily cost of a healthy diet that meets food group recommendations[8]. All three are based on the lowest cost combination of locally available food in each country.

Note that the Food Prices for Nutrition DataHub defines a fixed proportion, which is assumed to be the food expenditure share in lower-income households, of the poverty line as a food poverty line, and compares it with the costs of energy-adequate, nutrient-sufficient, and healthy diet to assess the food affordability, whereas we derive the income thresholds based on the cost indicators and food expenditure share in lower-income households and define it as the food poverty lines (FPLs).

The cost indicators to derive FPLs are based on the national average prices in 2017 expressed in purchasing power parity (PPP) dollars. To match our model, they are converted to the 2011 level in 2017 PPP dollars based on CPI adjustments ($c_{CPI,2017to2011}$), as shown in Eq. 6:

$$Cost_{i,2011,2017PPP} = Cost_{i,2017,2017PPP} \times c_{CPI,2017to2011}, \qquad \text{Eq. 6.}$$

where $Cost_{i,2011,2017PPP}$ is the cost level for dietary requirement *i* in 2011 in 2017 PPP dollars; it is not available in the World Bank Food Prices for Nutrition Data Bank [10]. $Cost_{i,2017,2017PPP}$ is the cost level i in 2017 in 2017 PPP dollars; and $c_{CPI,2017to2011}$ are the conversion factors for CPI.

$Cost_{i,2011,2017PPP}$ is then scaled to the price of a food basket as provided by the AIM-PHI (Eq. 7), to obtain the national FPL in future scenarios (Eq. 8),

$$Cost_{i,t,2017PPP} = Cost_{i,2011,2017PPP} \times \frac{p_{t,2017PPP,sc}}{p_{2011,2017PPP,sc}}, \qquad \text{Eq. 7.}$$

$$FPL_{i,t,2017PPP} = \frac{Cost_{i,t,2017PPP}}{Share_{r,"food"}}, \quad \text{Eq. 8.}$$

where $FPL_{i,t,2017PPP}$ is the food poverty line for dietary requirement i in time t in 2017 PPP, $Cost_{i,t,2017PPP}$ is the cost indicator for i in time t in 2017 PPP dollars; $p_{t,2017PPP,sc}$ is the food basket price in time t in 2017 PPP dollars in scenario sc; $p_{2011,2017PPP,b}$ is the food basket price in 2017 PPP dollars, which is the benchmark in scenario sc. $Share_{r,"food"}$ is the share of food expenditure share in lower income population estimated by World Bank [11].

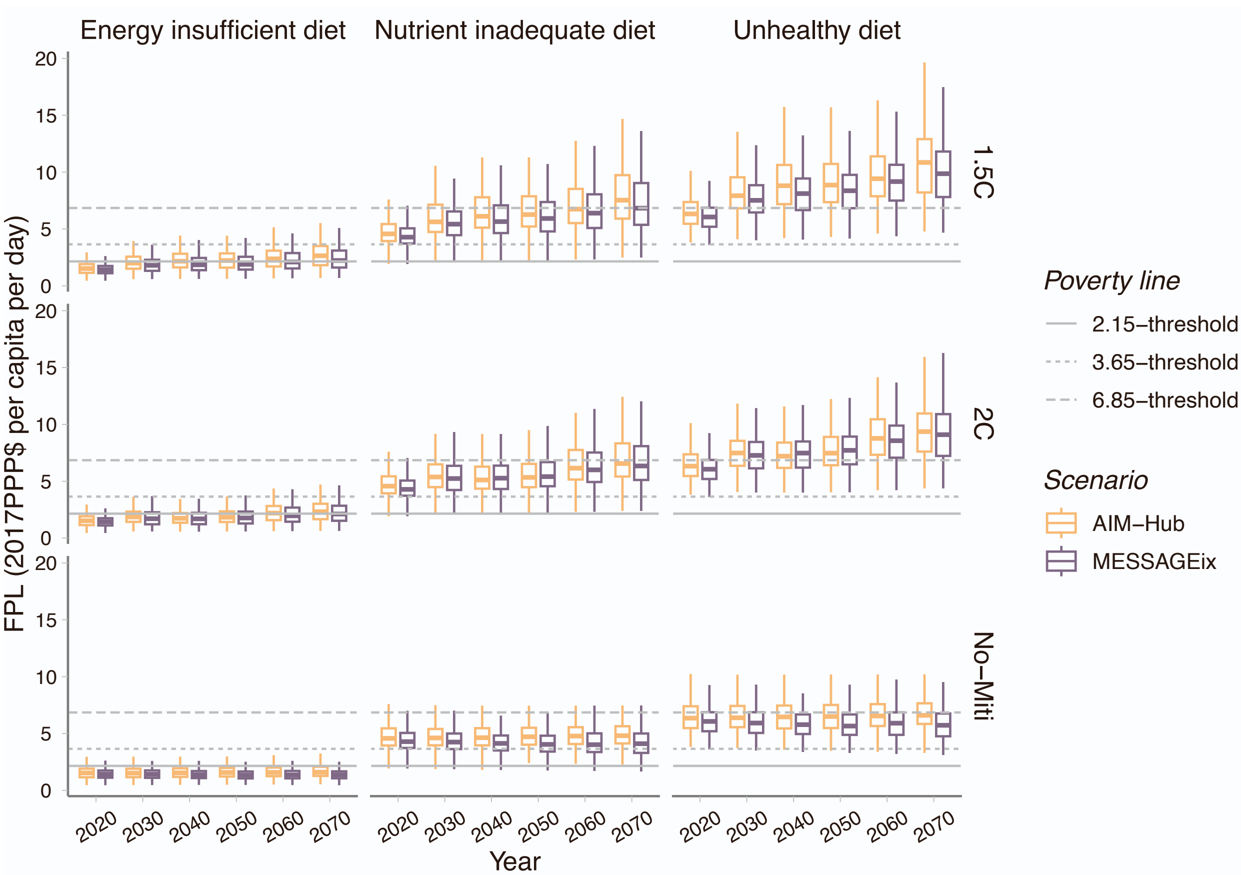

Figure S7 FPLs for different dietary requirements. In the No-Miti scenario, the median FPL for energy sufficiency is close to the international poverty line (2.15-threshold), the median FPL for nutrient adequacy is close to the poverty line for LMICs, and the median FPL for a healthy diet is close to the poverty line for UMICs. The FPLs decrease in the future in the No-Miti scenario due to increased productivity. But they increase in the mitigation scenarios, especially in the AIM-Hub scenarios, due to carbon pricing. More stringent mitigation leads to higher FPLs at all levels.

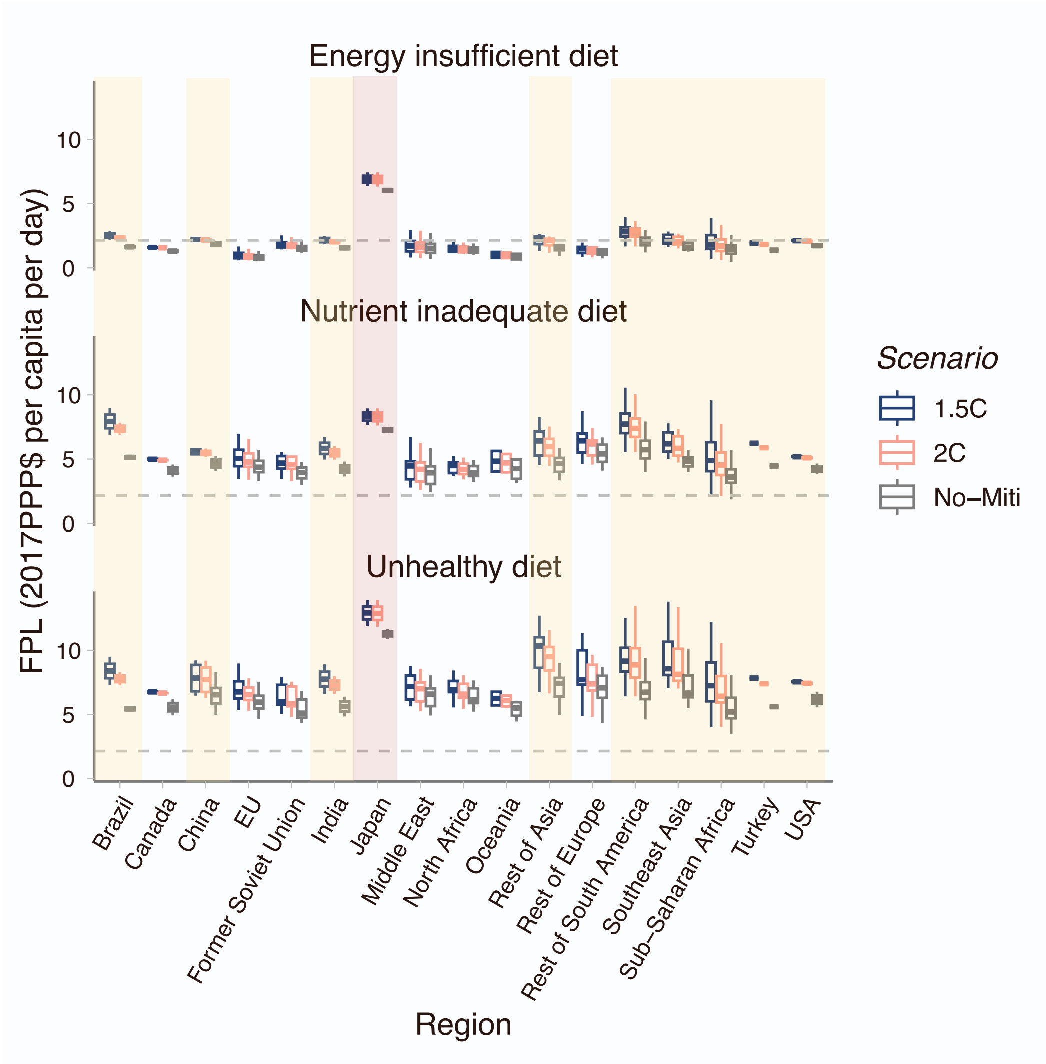

Figure S8 FPLs in 2030, in different regions. The box shows the range between the lowest and highest quartiles, with the bar in the middle representing the median FPLs across countries. The whiskers show the range between the lowest and highest extremes and the lowest and highest quartiles. The gray dashed line represents the international poverty line. Yellow shading: regions with large impacts from climate change mitigation; red shading: regions with a high FPL in the No-Miti scenario. Note that the carbon tax revenue redistribution does not affect the cost in this scenario, but it does change the food poverty projection by compensating for household consumption.

Regionally, three patterns can be observed: 1) a high FPL even without additional climate policies, as occurs in Japan, due to high prices and low food expenditure share (marked red in Figure S8); 2) a high FPL due to climate policies, such as in India, the Rest of Asia, the Rest of South America, Southeast Asia and Sub-Saharan Africa, etc. (marked yellow in Figure S8); 3) a modest or low FPL with a modest impact of climate policies. In countries with severe food poverty, the second pattern is seen most often, attributable to the drastic price increases in the agriculture sector.

The model estimation of food poverty and the percent of the population who cannot afford to meet certain dietary level from World Bank Food Prices for Nutrition Data Bank [10] are compared to estimate model performance (Figure S9).

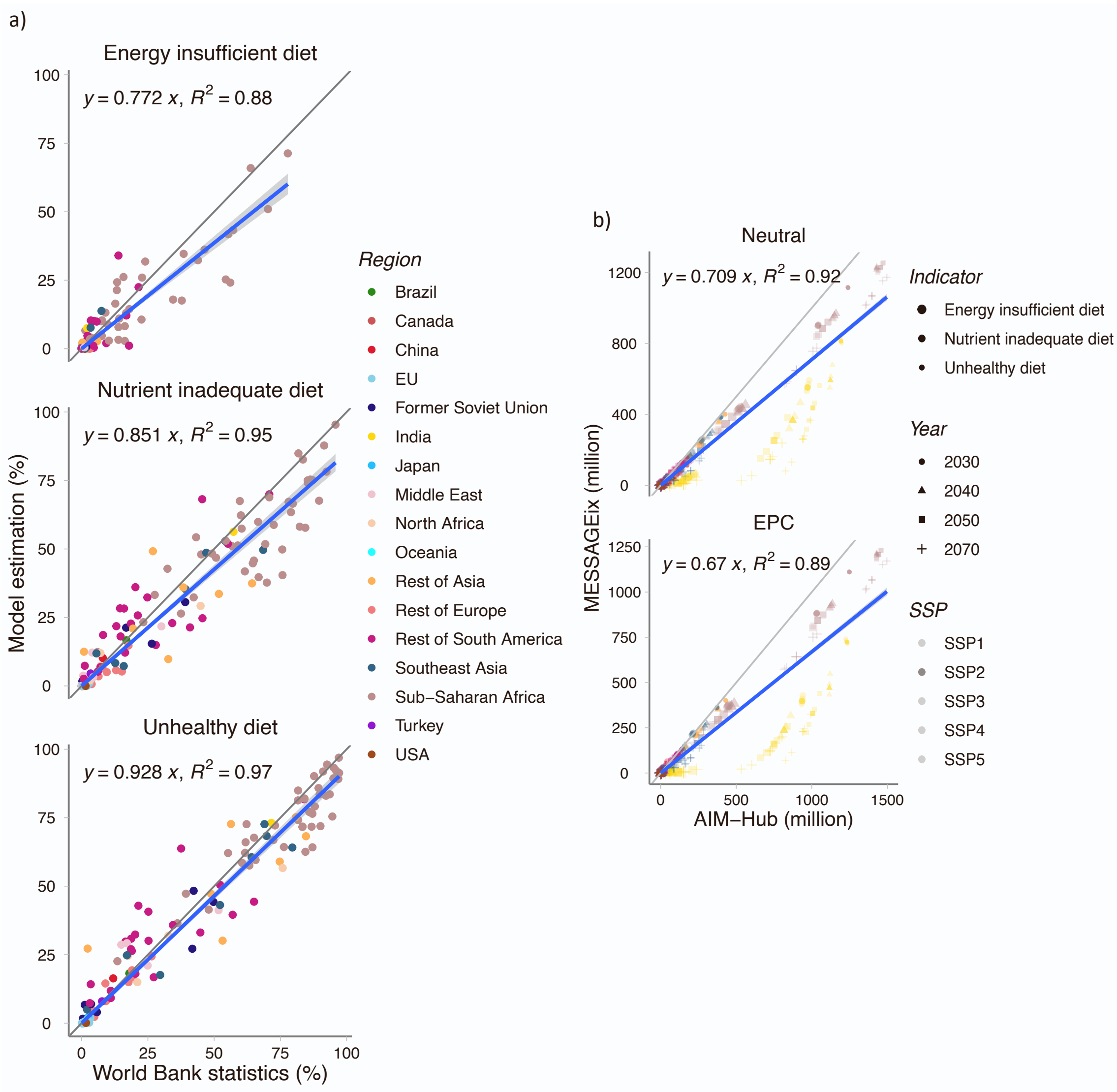

Figure S9 Food poverty projection assessment. a) Comparison of model estimation with World Bank statistics. b) Comparison between AIM-Hub projection (x-axis) and MESSAGEix projection (y-axis).

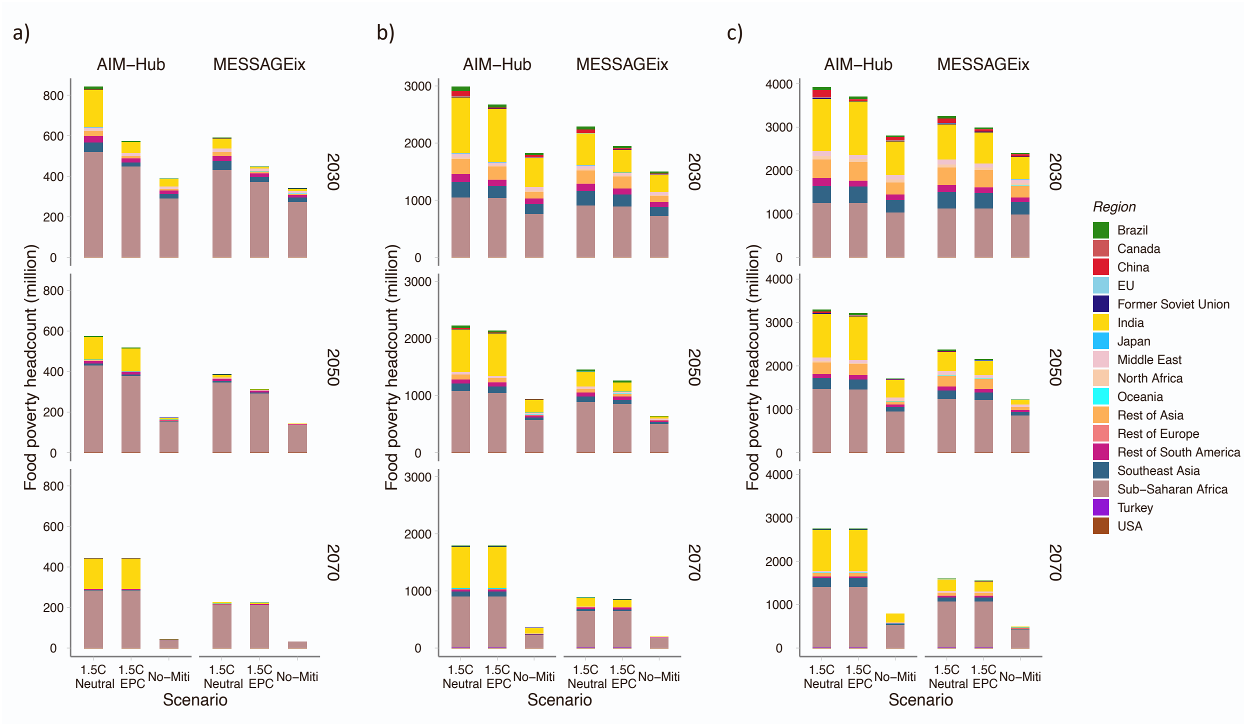

Figure S10 Food poverty projections in both models for population cannot afford a) energy sufficient, b) nutrient adequate, and c) healthy diets.

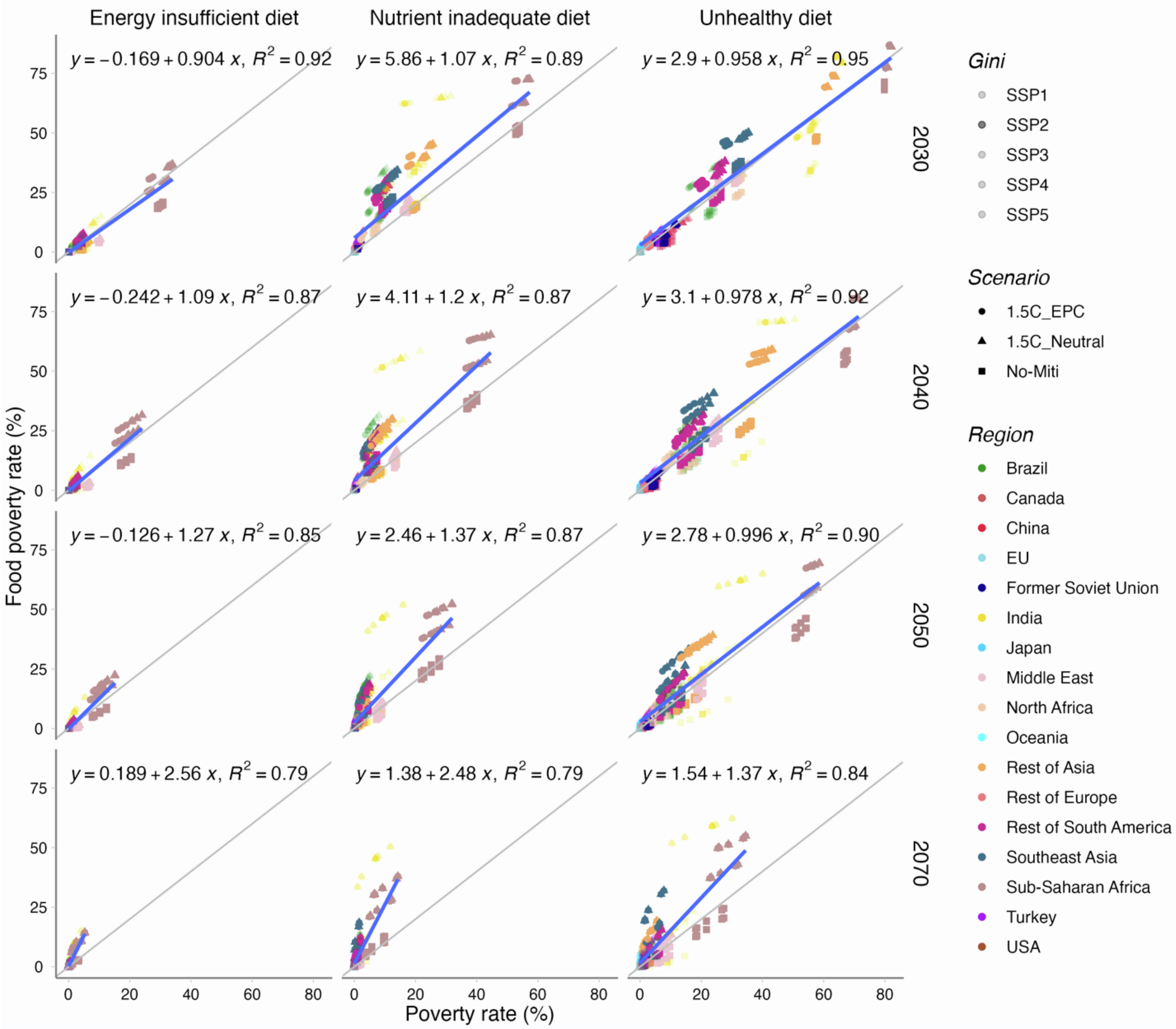

Figure S11 Comparison between food poverty and poverty at different levels. Based on Figure S7, food poverty measured by energy sufficiency is compared with poverty measured by the international poverty line. Food poverty measured by nutrient adequacy is compared with poverty measured by the 3.65-threshold, and food poverty measured by a healthy diet is compared with poverty measured by the 6.85-threshold. Food poverty is strongly correlated to and generally more severe than poverty, especially in India, where FPLs increase significantly in mitigation scenarios.

Supplemental Notes

Note S1 Comparisons of the two upstream models

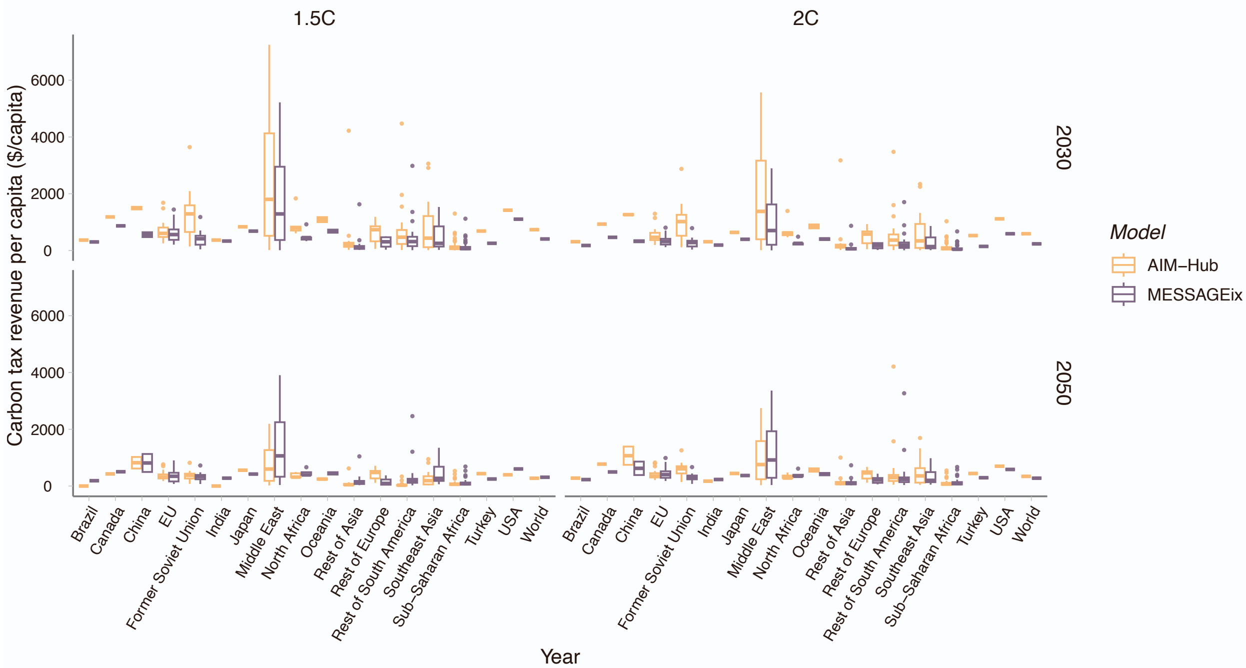

Figure S12 Carbon tax revenues from FFI CO2 emissions in the two upstream models.

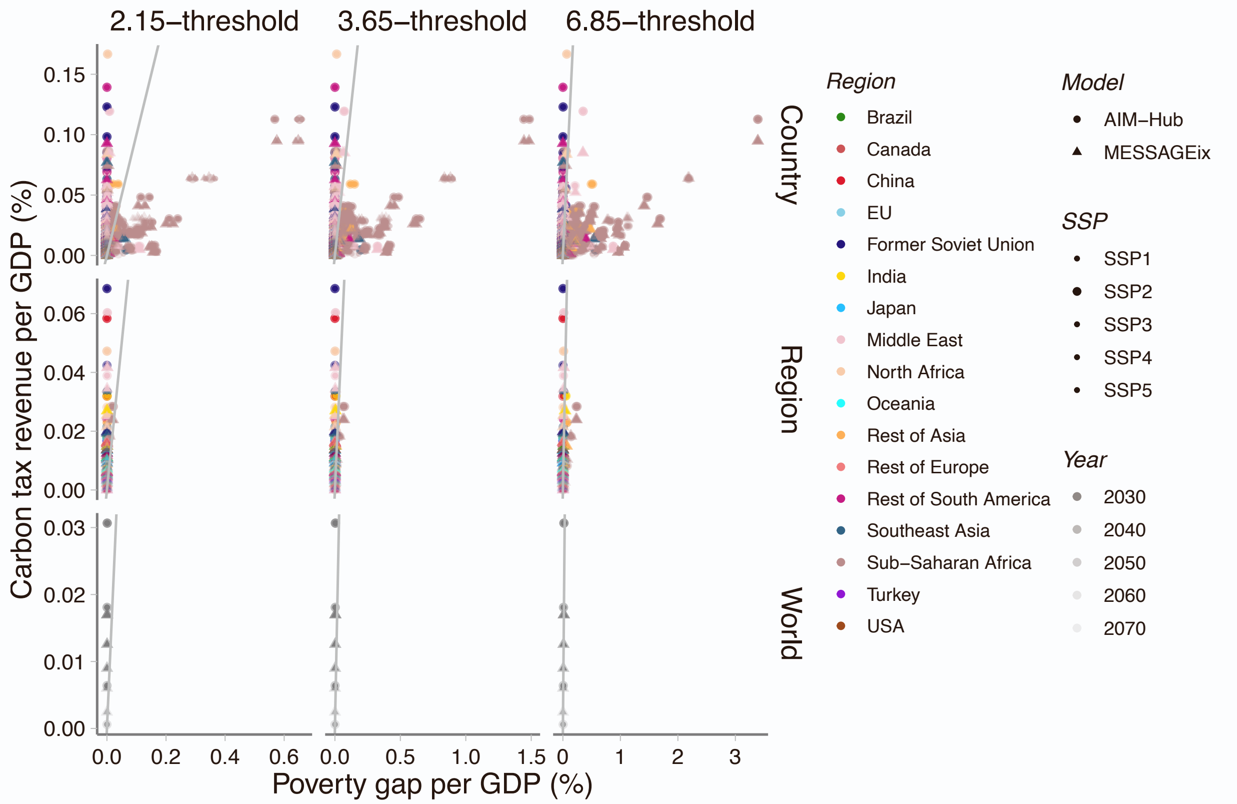

Figure S13 Comparison between the poverty gap (x-axis) and carbon tax revenue (y-axis) under different assumptions of international transfer of carbon tax revenue in the 1.5˚C scenario. The grey line shows x = y. The "Country" panel indicates domestic carbon tax revenue and poverty gap. The "Region" panel indicates the regional carbon tax revenue and regional poverty gap, and the "World" panel indicates the global carbon tax revenue and global poverty gap. While the domestic carbon tax revenues do not suffice to fill in the domestic poverty gap in some Sub-Saharan Africa countries, regional carbon tax revenues could fill in the regional poverty gap measured at the international poverty line, and global carbon tax revenues could be enough to fill in the global poverty gap for higher poverty lines. This indicates a huge potential of eliminating poverty if the carbon tax revenues could be freely allocated internationally to compensate for consumptions of the lower-income population.

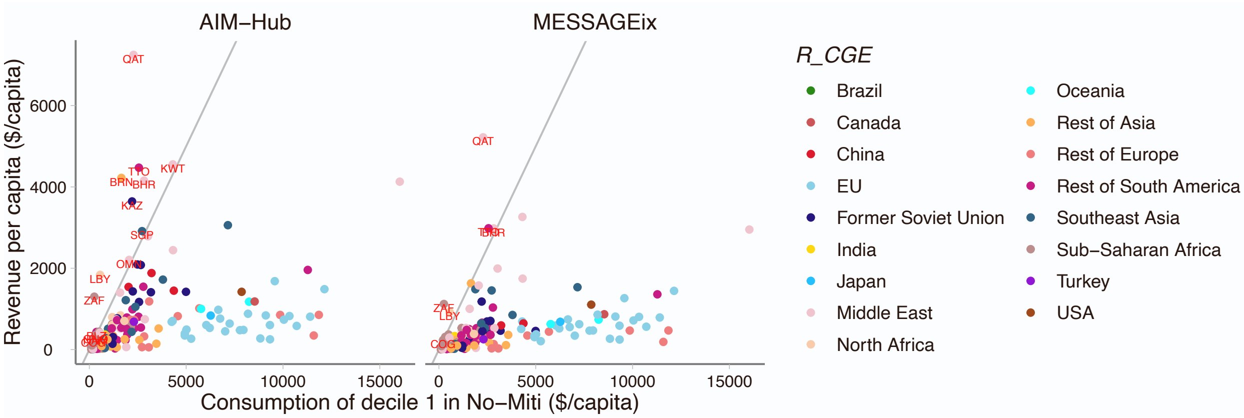

Figure S14 Comparison between the consumption of decile 1 in No-Miti scenario (x-axis) and carbon tax revenue per capita in 1.5˚C scenario (y-axis).

Significant impacts were observed in decile 1, the lowest income decile, due to either low household budgets (e.g., in South Africa and Libya) or high carbon tax revenues from the FFI sector (e.g., in Qatar and Kuwait). In the neutral redistribution scenario, the substantial consumption loss in decile 1 can be attributed to the macroeconomic loss far exceeding the carbon tax revenue.

For the EPC scenarios, as can be seen in Figure S14, two types of country demonstrate a high effectiveness of equal per capita (EPC) redistribution. Type-A countries are low-income countries with an extremely low household budget in decile 1, such as Libya (LBY) in North Africa, Belize (BLZ) in the Rest of South America, and Sub-Saharan African countries such as South Africa (ZAF), Republic of the Congo (COG), Equatorial Guinea (GNQ), and Namibia (NAM). Type-B countries are countries with huge FFI production and consumption, leading to extremely high carbon tax revenues from FFI, which are recycled in this study. These countries are concentrated in the Middle East, such as Qatar (QAT), Bahrain (BHR), Kuwait (KWT), Oman (OMN) and Brunei (BRN) in Rest of Asia.

For the neutral redistribution, it can be seen in Figure S15 that Uzbekistan (UZB) in Former Soviet Union countries, Syria (SYR) in the Middle East, Libya (LBY) in North Africa, Trinidad and Tobago (TTO) in the Rest of South America, and Somalia (SOM) in Sub-Saharan Africa generate carbon tax revenues of more than 10% of the total national consumption. Comparing the national consumption loss rate (compared to total national consumption in the No-Miti scenario) with the revenues per No-Miti national consumption (Figure S16), a huge net consumption loss (due to the huge macroeconomic loss) is apparent in many countries, especially in the AIM-Hub scenario. The exceptions are the Middle East, some Former Soviet Union countries, and the Rest of South American countries, due to the huge reliance on FFI sectors.

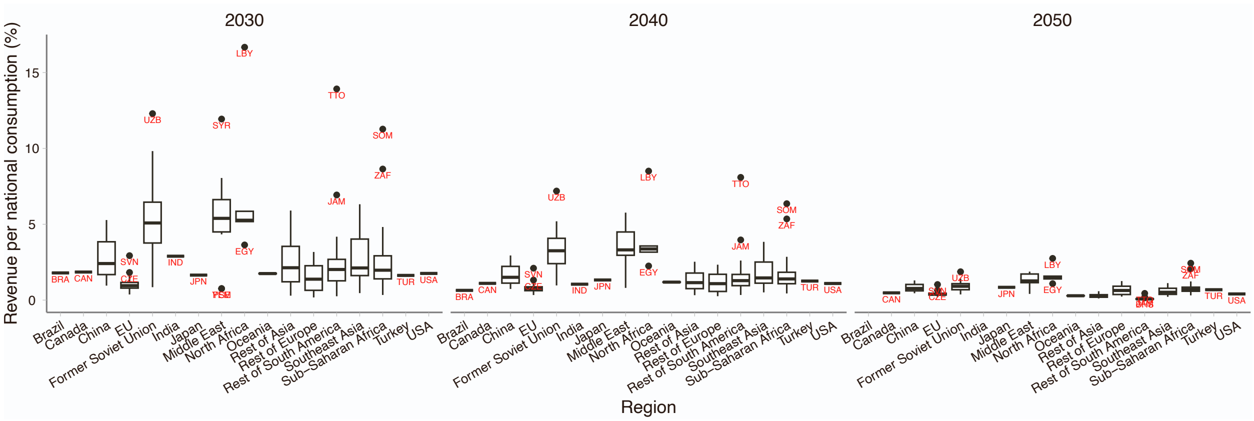

Figure S15 Proportion of revenues (in distribution-neutral scenario) compared to household consumption in No-Miti scenario.

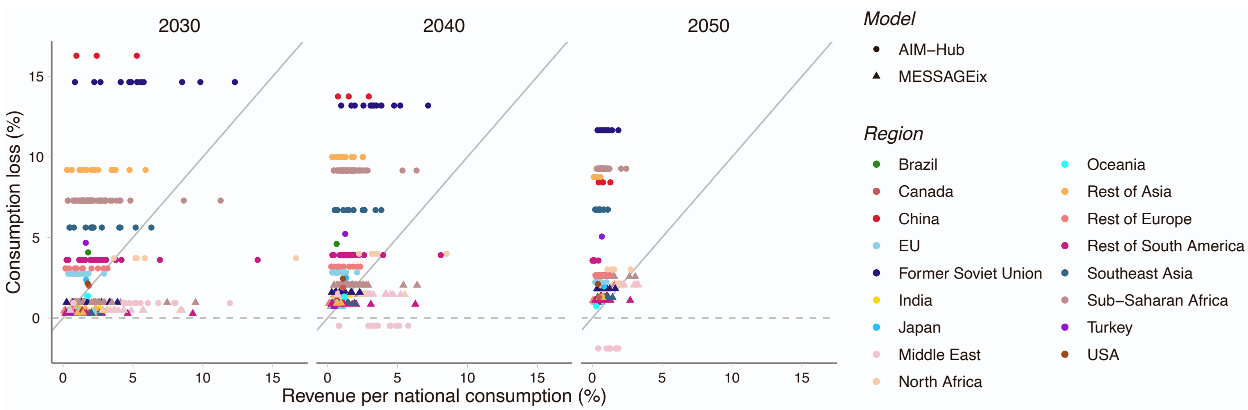

Figure S16 Comparison between revenues per No-Miti national consumption (x-axis) and national consumption loss rate (y-axis) Note that national consumption loss rate equals the regional consumption loss rate but revenues per No-Miti national consumption are calculated per country. Net consumption loss can be calculated by y-value minus x-value.

Table S3 Top 20 countries with the highest PRT projections in 2030

Region	Redistribution	AIM-Hub	MESSAGEix
China	Neutral	1	0
Former Soviet Union	Neutral	12	1
India	Neutral	1	0
Sub-Saharan Africa	Neutral	2	16
Rest of Asia	Neutral	4	0
Brazil	Neutral	0	1
Rest of South America	Neutral	0	1
Southeast Asia	Neutral	0	1
Sub-Saharan Africa	EPC	15	14
Rest of South America	EPC	2	2
Rest of Asia	EPC	2	1
Southeast Asia	EPC	1	1
Rest of Europe	EPC	0	1
Middle East	EPC	0	1

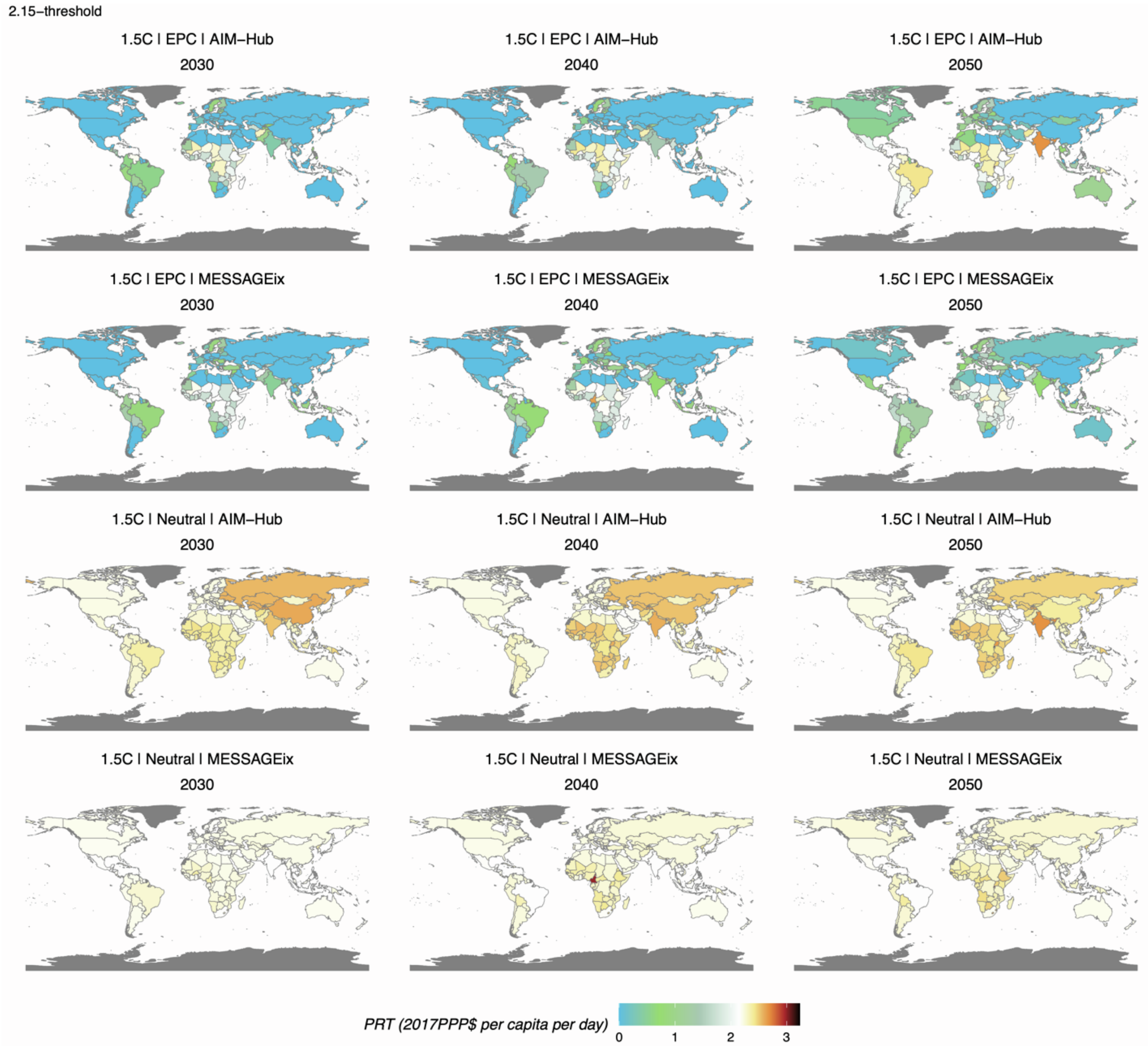

Figure S17PRTs for the international poverty line (2.15-threshold) in 1.5°C scenarios.

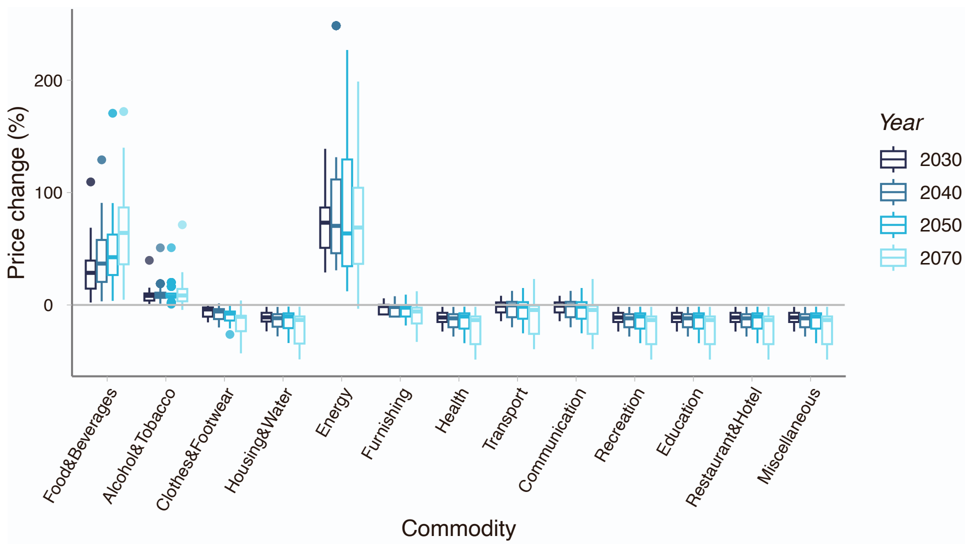

Figure S18 Price changes of all commodities in both models. MESSAGEix provides only prices related to agriculture and energy sectors, the projections of the price index are compared only with respect to food and to energy (Figure S19).

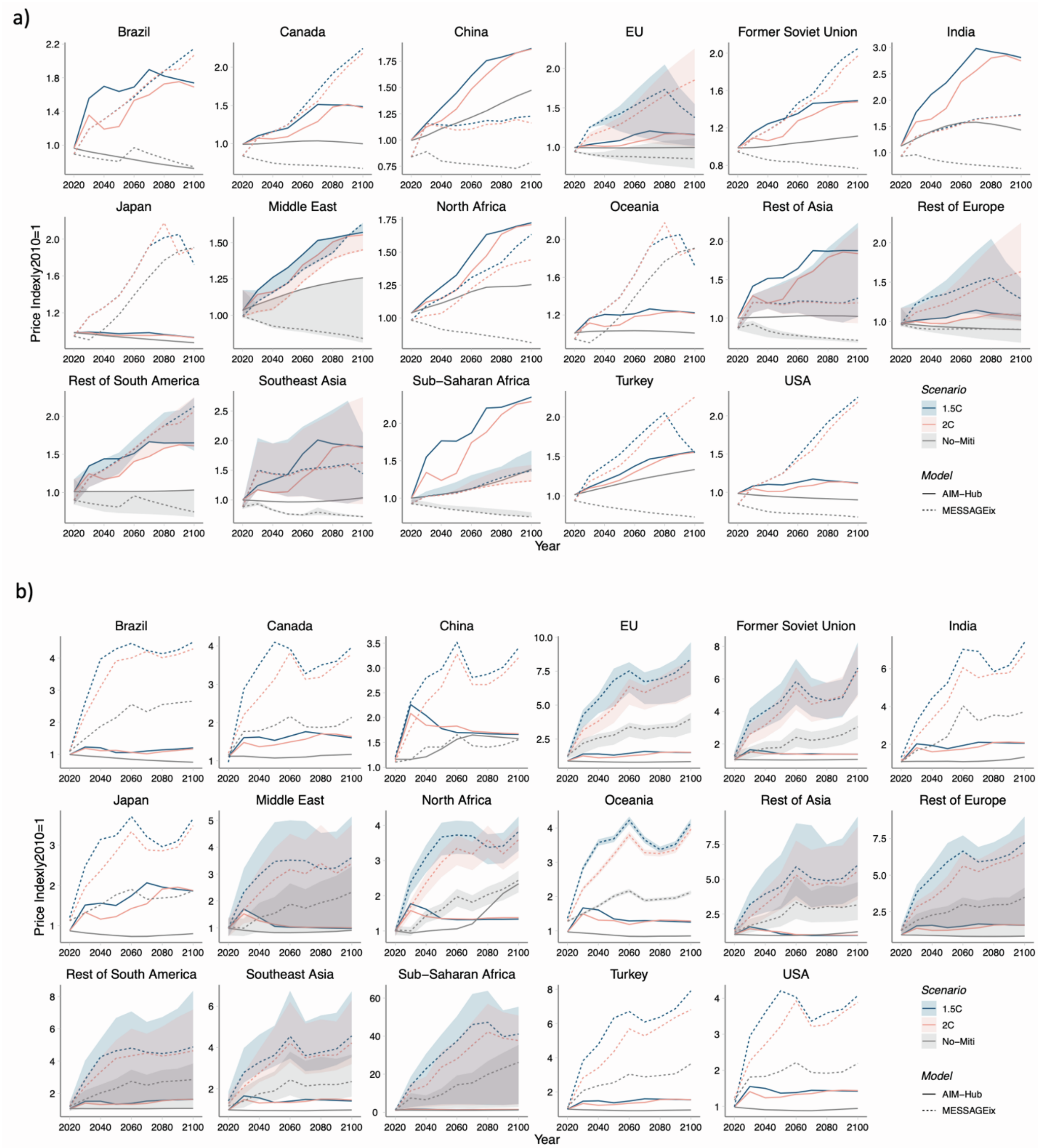

Figure S19 Different projections of the price index for a) food prices and b) energy prices in the two upstream models. Regional aggregates are defined according to AIM-Hub definitions, to which the information from MESSAGEix was mapped. The solid lines show the AIM-Hub projections, the ribbons the range of the MESSAGEix projections, and the dashed lines the regional median of the MESSAGEix projections.

Note S2 Marginal policy effects

Marginal policy effects are investigated by running a linear regression of the poverty headcount and the Gini coefficient vs. the carbon price, as a proxy for policy stringency, as shown in Eq. 8. An AIM-Hub scenario set with the remaining global carbon budgets ranging from 400 Gt to 1600 Gt CO_2eq in this century is applied.

$$\Delta y_{c,t,R,sc} = \alpha_{c,t,R} \times x_{c,t,R,sc} + \beta_{c,t,R,P} + \gamma_{c,t,R}, \qquad \text{Eq. 9.}$$

where $\Delta y_{c,t,R,sc}$ is the absolute change in the poverty headcount or Gini coefficient with revenue redistribution *c*, in time slice t, region R, and scenario *sc*; $x_{c,t,R,sc}$ is the CO_2 reduction rate with revenue redistribution *c*, in time slice t, region R, and scenario *sc*; $\alpha_{c,t,R}$ is the marginal policy effects on *y*; $\beta_{c,t,R,P}$ is the fixed effect of the policy package; and $\gamma_{c,t,R}$ is the country-fixed effect.

For the calculation of marginal policy effects, a policy package (Full Combo) is explored that integrated multiple socioeconomic-technological transitions, including energy-demand-change (EDC), energy-supply-change (ESC), food-system-transformation (FST), and additional-capital-formation (ACF), as an alternative to EPC redistribution, and as a countermeasure to the negative policy impacts in the AIM-Hub model.

EDC indicates accelerated energy technology innovations, demand-side energy efficiency improvements, energy service demand reduction, and enhancement of electrification. ESC assumes a sharp decrease of costs associated with renewable energy generation, the storage of variable types of renewable energy, and carbon dioxide capture and storage (CCS)-related technology. FST is focused on environmental and health awareness by the public and the corresponding changes in food consumption, such as reductions in livestock-based food consumption and food waste to meet SDG11. ACF prioritizes environmentally responsible investments for future generations rather than current consumption, thus reflecting a general awareness of and attention to ESG factors. Further details can be found in the work of Fujimori and colleagues [12].

The socioeconomic-technological transitions are assumed in the upstream model while demand reductions are not represented at the household level in AIM-PHI, resulting in an innate inconsistency in the demand-side narrative. However, this socioeconomic-technological transition package proved in the previous study[12] to be effective in reducing macroeconomic loss associated with climate policies, which was the main contributor to poverty. The qualitative conclusion is that such socioeconomic-technological transitions have the potential to offset adverse climate-policy impacts, such as increasing poverty.

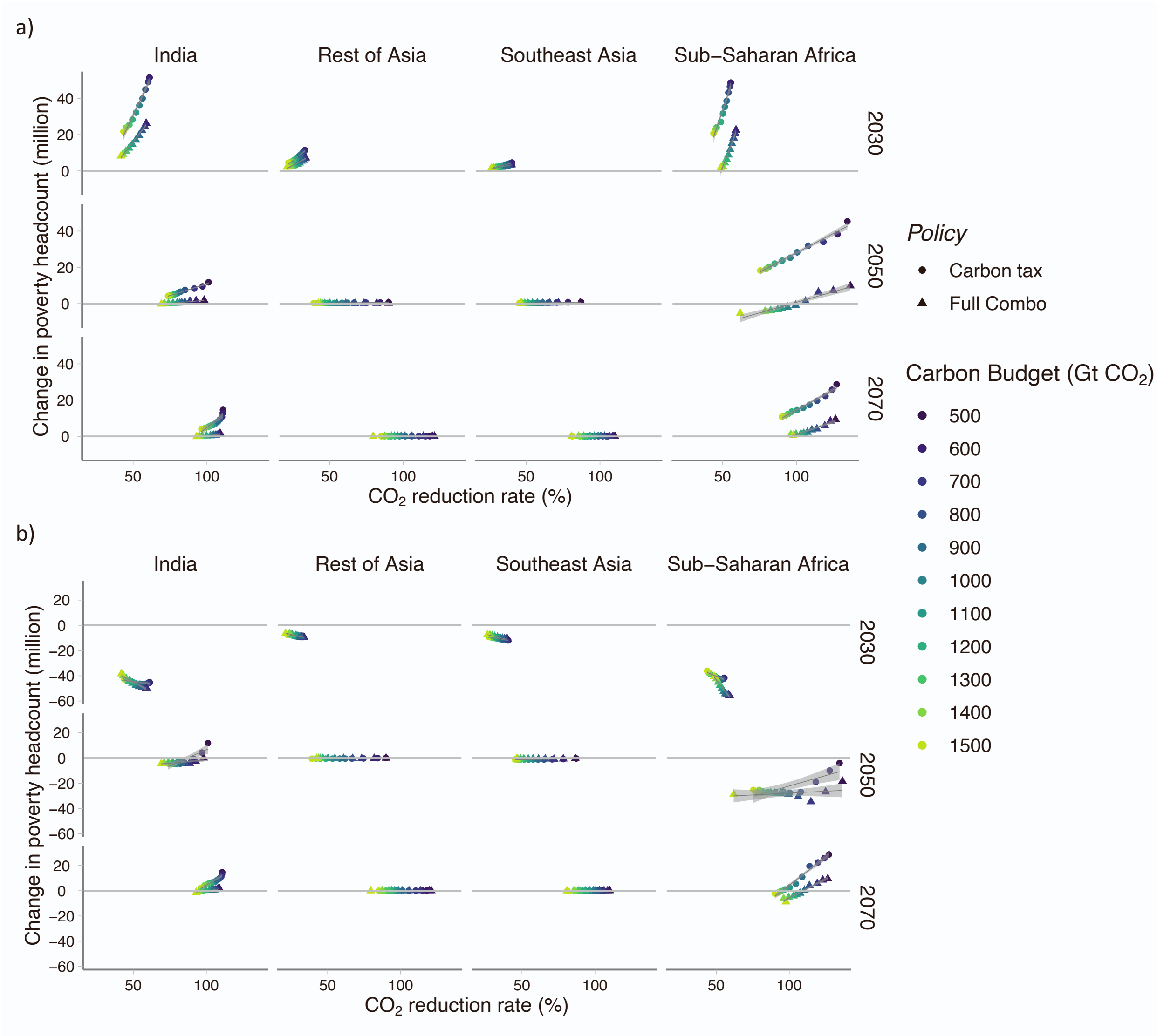

Figure S20 Policy impacts on the poverty headcount under a) neutral carbon revenue redistribution and b) EPC carbon tax revenue redistribution. The four modeling regions where policy impacts are the most prominent are selected. The socioeconomic-technological transitions package effectively reduces the adverse policy impacts on poverty headcount under the neutral redistribution scheme, but it is less powerful when an EPC carbon revenue redistribution is already in place. However, an advantage of this transition package, compared with an EPC redistribution, is that its benefits persist in the long-term.

Table S4 Parameter estimates on the relation between additional poverty headcount and policy stringency with neutral redistribution

		2.15-threshold | Neutral | Poverty (million)			
Region	Year	Marginal policy effect	Full Combo	Region-fixed effect	Adj. R-square
Sub-Saharan Africa	2030	1.90	-30.8	-60.3	0.936
	2050	0.247	-27.7	5.14	0.848
India	2030	1.38	-16.4	-36.8	0.964
	2050	0.172	-5.87	-7.59	0.936
Rest of Asia	2030	0.532	-3.53	-7.15	0.952
	2050	0.00724	-0.330	0.0150	0.937
Southeast Asia	2030	0.183	-0.797	-3.13	0.965
	2050	0.0105	-0.226	-0.146	0.951
China	2030	0.0540	-0.233	-1.25	0.968
	2050	0.00	-0.0107	-0.0149	0.898
Rest of South America	2030	0.0409	-0.478	-0.483	0.903
	2050	0.00357	-0.24	0.0308	0.877
Brazil	2030	0.0187	-0.291	-0.354	0.776
	2050	0.00121	-0.106	-0.0128	0.674
North Africa	2030	0.0122	-0.298	-0.0894	0.979
	2050	0.00	-0.0556	-0.00540	0.966
Former Soviet Union	2030	0.0103	-0.0981	-0.151	0.956
	2050	0.00	-0.0411	0.0277	0.955
Middle East	2030	0.00531	-1.06	0.171	0.991
	2050	-0.00572	-1.44	0.260	0.961
Turkey	2030	0.00111	-0.00901	-0.0119	0.982
	2050	0.00	-0.00639	0.00	0.953
Rest of Europe	2030	0.00	0.00	0.00	0.96
	2050	0.00	0.00	0.00	0.953
EU	2030	0.00	0.00	0.00	0.987
	2050	0.00	0.00	0.00	0.694
Japan	2030	0.00	0.00	0.00	0.979
	2050	0.00	0.00	0.00	0.868
USA	2030	0.00	0.00	0.00	0.978
	2050	0.00	0.00	0.00	0.88
Canada	2030	-	-	-	-
	2050	-	-	-	-
Oceania	2030	-	-	-	-
	2050	-	-	-	-

Table S5 Parameter estimates on the relation between additional poverty headcount and policy stringency with EPC redistribution

		2.15-threshold | EPC | Poverty (million)			
Region	Year	Marginal policy effect	Full Combo	Region-fixed effect	Adj. R-square
Sub-Saharan Africa	2030	-0.563	-7.85	-12.6	0.701
	2050	0.155	-5.91	-36.8	0.366
India	2030	-0.330	-1.52	-27.8	0.410
	2050	0.337	-1.52	-29.5	0.602
Rest of Asia	2030	-0.224	0.344	-2.23	0.868
	2050	0.00883	0.026	-0.898	0.655
Southeast Asia	2030	-0.219	1.05	-3.31	0.860
	2050	0.0129	0.296	-1.80	0.609
Rest of South America	2030	-0.103	1.07	-1.02	0.922
	2050	0.0130	0.224	-2.04	0.320
Brazil	2030	-0.0470	0.790	-1.22	0.818
	2050	0.00676	0.199	-1.57	0.397
Turkey	2030	-0.00354	0.0266	-0.00988	0.974
	2050	0.00	0.0146	-0.0302	0.886
China	2030	-0.00253	0.0260	-1.48	0.552
	2050	0.00	0.00364	-0.0203	0.773
Rest of Europe	2030	0.00	0.00127	-0.00483	0.887
	2050	0.00	0.00	-0.00161	0.878
Oceania	2030	0.00	0.00	0.00	0.847
	2050	-	-	-	-
EU	2030	0.00	0.00	0.00	0.962
	2050	0.00	0.00	0.00	0.933
Japan	2030	0.00	0.00	0.00	0.930
	2050	0.00	0.00	0.00	0.967
USA	2030	0.00	0.00	0.00	0.907
	2050	0.00	0.00	0.00	0.788
Former	2030	0.00351	-0.0405	-0.296	0.262
	2050	0.00	0.00801	-0.0859	0.806
North Africa	2030	0.0227	-0.192	-2.74	0.610
	2050	0.00	0.0463	-0.213	0.914
Middle East	2030	0.0370	-1.20	-3.00	0.871
	2050	0.00	-0.677	-1.73	0.852
Canada	2030	-	-	-	-
	2050	-	-	-	-

Table S6 Parameter estimates on the relation between the change in Gini (regional median) and policy stringency with neutral redistribution

Region	Year	Inequality | Neutral | Gini (point) Marginal policy effect	Full Combo	Region-fixed effect	Adj. R-square
Sub-Saharan Africa	2030	0.0156	-0.171	-0.590	0.563
	2050	0.00	-0.00972	0.00576	0.0213
Rest of Asia	2030	0.0118	-0.102	-0.156	0.298
	2050	0.00	0.0115	0.00	0.00610
India	2030	0.00762	-0.0832	-0.186	0.973
	2050	-0.0114	0.378	0.611	0.976
Brazil	2030	0.00695	-0.0995	-0.202	0.848
	2050	0.000622	-0.0302	-0.0266	0.737
Japan	2030	0.00438	-0.0242	-0.0447	0.978
	2050	0.00157	-0.0332	-0.00773	0.947
Southeast Asia	2030	0.00337	-0.0323	-0.0508	0.230
	2050	0.00	0.00	0.00804	-0.00434
Rest of South America	2030	0.00191	-0.0271	-0.0342	0.193
	2050	0.00	-0.00684	-0.00585	0.00586
Middle East	2030	0.00101	0.00390	-0.00883	0.0338
	2050	0.00	-0.00436	-0.00363	-0.00761
EU	2030	0.00	-0.00160	0.00369	0.110
	2050	0.00	0.00913	0.0139	0.109
Oceania	2030	0.00	-0.00326	-0.0131	0.359
	2050	-	-	-	-
Canada	2030	0.00	0.00	-0.00305	0.900
	2050	-	-	-	-
Rest of Europe	2030	0.00	-0.00469	0.00	-0.00423
	2050	0.00	-0.0126	0.00	0.570
Turkey	2030	0.00	0.00	0.00177	1.00
	2050	0.00	-0.0128	0.00418	0.990
North Africa	2030	0.00	0.00	0.0258	-0.0275
	2050	0.00	0.0466	0.00	0.925
China	2030	0.00	-0.00395	0.00638	-0.0440
	2050	0.00	-0.00752	-0.0164	-0.0447
Former Soviet Union	2030	0.00	0.00502	-0.00553	-0.00252
	2050	0.00	0.00998	0.00	-0.00197
USA	2030	-	-	-	-
	2050	-	-	-	-

Table S7 Parameter estimates on the relation between change in Gini (regional median) to policy stringency with the EPC redistribution

Region	Year	Inequality | EPC | Gini (point) Marginal policy effect	Full Combo	Region-fixed effect	Adj. R-square
Turkey	2030	-0.219	1.68	2.38	0.991
	2050	-0.02	1.71	-2.25	0.914
Sub-Saharan Africa	2030	-0.191	1.76	3.81	0.0376
	2050	-0.00511	1.32	-2.68	0.0975
Southeast Asia	2030	-0.190	0.865	1.14	0.0990
	2050	0.0116	1.28	-3.78	0.147
China	2030	-0.168	1.54	-0.0737	0.326
	2050	-0.00432	1.88	-3.80	0.844
Rest of Asia	2030	-0.167	0.724	0.286	0.0350
	2050	0.00580	0.761	-2.11	0.0483
India	2030	-0.143	0.752	-0.565	0.887
	2050	0.0689	1.69	-9.07	0.669
Rest of South America	2030	-0.138	1.45	0.293	0.107
	2050	0.0168	1.00	-3.71	0.165
Middle East	2030	-0.138	0.746	-3.28	0.0278
	2050	0.00	1.89	-5.08	0.0848
USA	2030	-0.11	0.89500	0.288	0.987
	2050	0.00733	0.747	-2.32	0.800
Oceania	2030	-0.101	0.912	1.30	0.944
	2050	0.00636	0.679	-2.12	0.737
Japan	2030	-0.0956	0.801	0.652	0.975
	2050	-0.00764	0.643	-1.23	0.960
Brazil	2030	-0.0932	1.56	-0.573	0.831
	2050	0.0189	1.06	-5.15	0.449
Rest of Europe	2030	-0.0881	0.85	0.744	0.0890
	2050	-0.00678	0.856	-1.22	0.195
Canada	2030	-0.0834	0.842	-0.0998	0.993
	2050	0.00426	0.710	-2.05	0.691
EU	2030	-0.0638	0.684	0.141	0.3690
	2050	-0.00156	0.540	-1.18	0.547
Former Soivet Union	2030	-0.0327	0.288	-3.86	-0.00194
	2050	0.0142	1.55	-4.83	0.243
North Africa	2030	-0.000853	-0.00485	-7.08	-0.0171
	2050	-0.0280	1.96	-2.88	0.174

Note S3 Regional outputs of the Gini coefficient

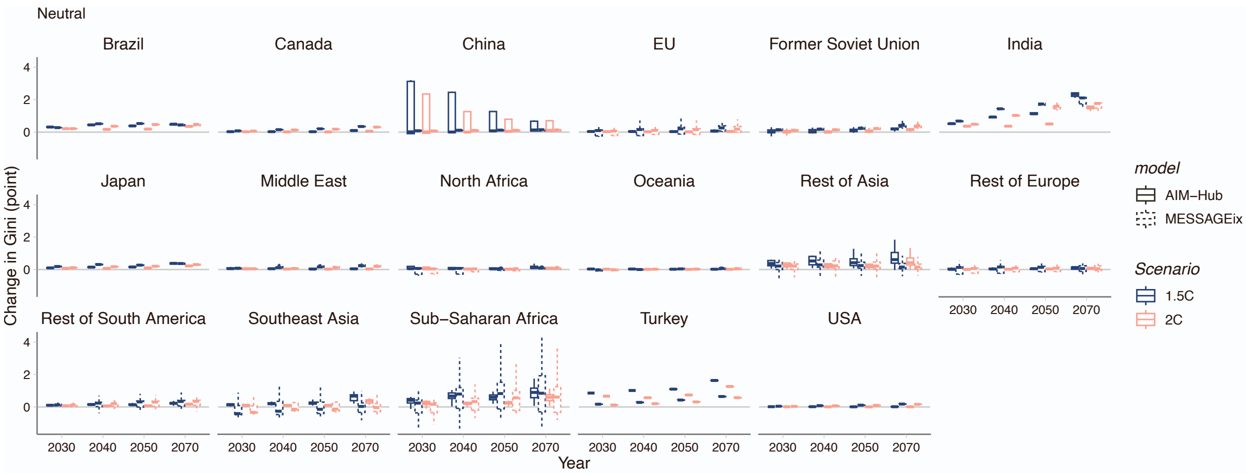

Figure S21 Changes of Gini coefficient in AIM-Hub by modeling region under a neutral carbon revenue redistribution.

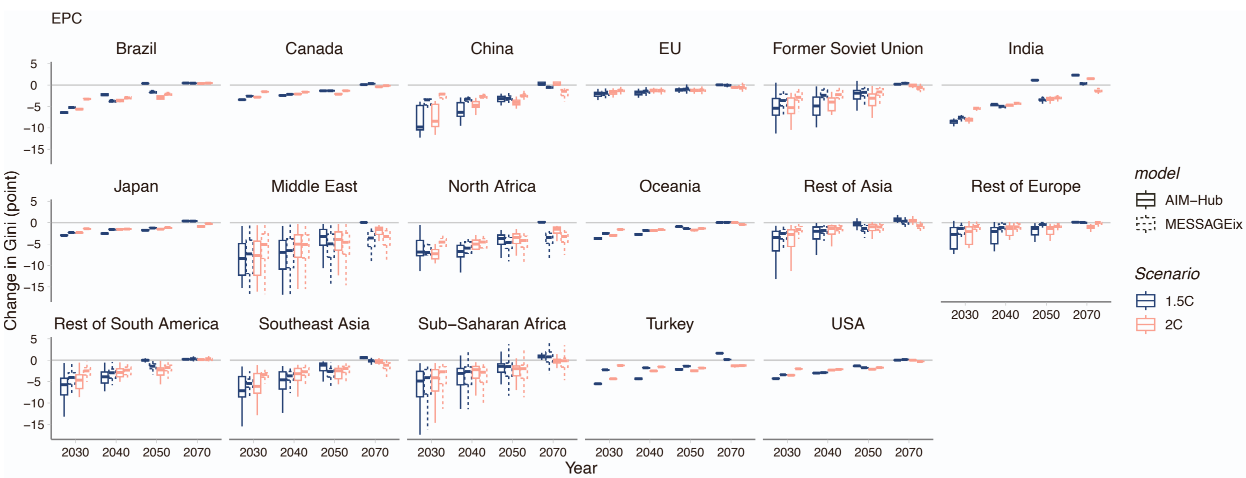

Figure S22 Changes of Gini coefficient in AIM-Hub by modeling region under the EPC carbon revenue redistribution.

Note S4 Robustness analysis and model-specific tendencies

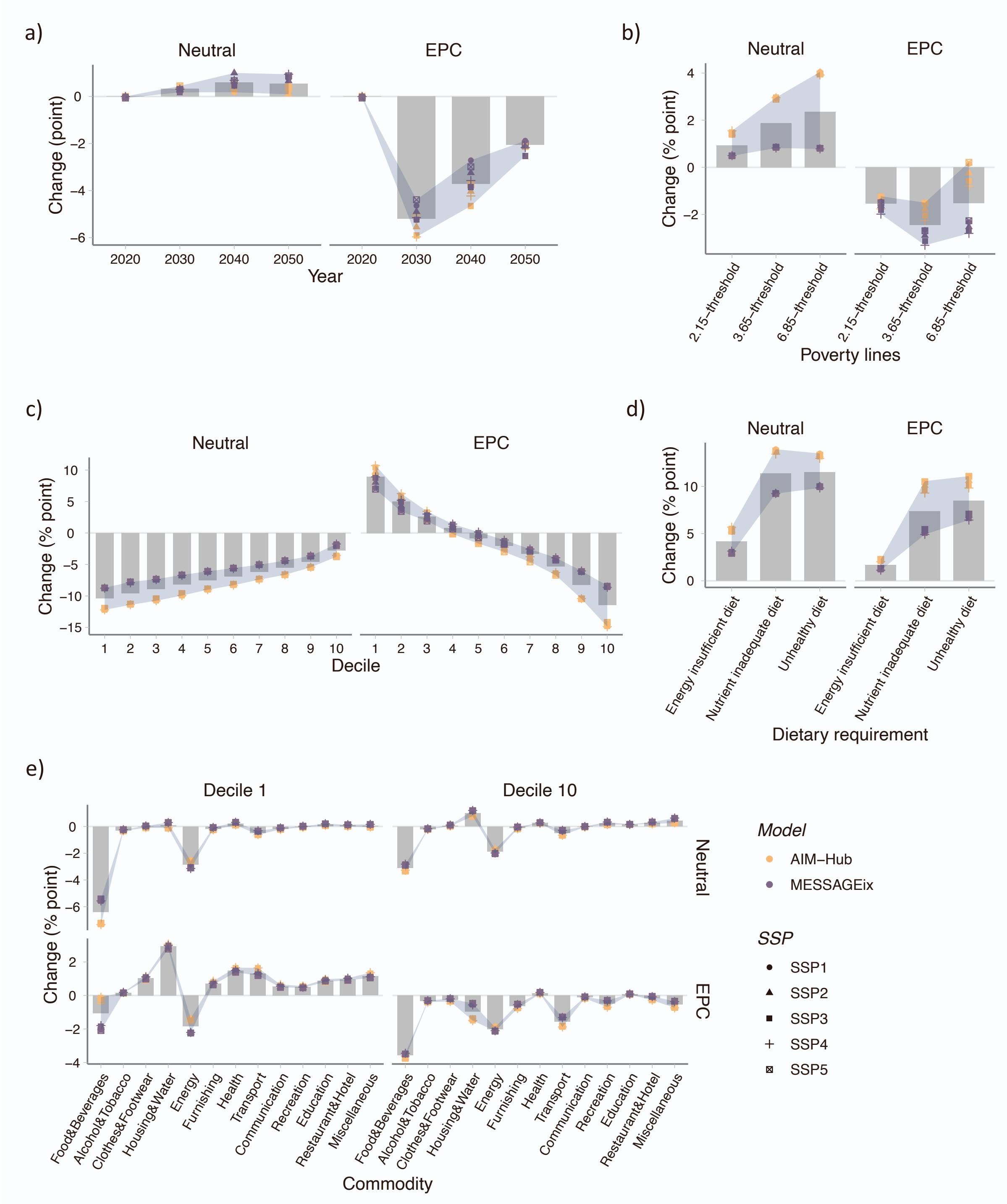

Figure S23 Sensitivity of the mitigation impacts. a) Changes in the Gini coefficients from 2020 to 2050. b) Changes in the poverty rate measured by different poverty lines in 2030. c) Changes in household consumption by income deciles in 2030. d) Changes in food poverty measured by different dietary requirements. Changes in household consumption by income deciles in 2030. e) Contributions of each commodity-wise consumption to total household consumption loss in Decile 1 (lowest decile) and Decile 10 (highest decile). Shaded areas mark the range between the maximum and minimum. The grey columns show the median of projections across models and SSPs.

The following model-specific tendencies in AIM-PHI model were identified from a comparison of the two models. First, poverty projections in AIM-PHI are more sensitive to macroeconomic income losses than to price changes, although strong regressive effects from rising food and energy prices to some extent add to the global poverty headcount. A mitigation scenario with net economic benefits, such as a scenario with a huge spillover from a low-carbon innovation [13], may result in a decrease in the poverty population. Second, inequality projections in AIM-PHI are largely decided by household consumption preferences and price changes, especially prices in agriculture, energy, and service sectors. This is because AIM-PHI is an expenditure-based inequality assessment tool that does not distinguish among the different household income sources or the consequent heterogeneous responses of household income.

Emmerling and coworkers identified four types of model in their comparisons of inequality models, with the aim of identifying the uncertainties and robustness of inequality assessments in climate change mitigation scenarios [14]. A crucial aspect of our analysis is its focus on comprehending the robustness and biases inherent in the AIM-PHI, by applying various climate policy scenarios to the same model. This approach allowed us to identify the sources of uncertainties and to draw robust conclusions.

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