Assessing the Distributional Implications of Carbon Pricing Strategies for Mitigating Global Greenhouse Gas Emissions

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Abstract

This paper assesses the distributional implications of a wide array of carbon pricing mechanisms aimed at curbing global greenhouse gas (GHG) emissions. By integrating a general equilibrium model with a global microsimulation, we investigate the effects of these policies on poverty and inequality levels across different regions. Our analysis reveals that while carbon mitigation measures generally have adverse but marginal impacts on global poverty, the magnitude of these effects varies significantly among countries. Under a scenario aligned with current nationally determined contributions, we project a modest increase in extreme poverty, impacting approximately 5 million individuals by 2050. A more ambitious trajectory targeting a 2°C cap on temperature rise could double the impact on poverty to 10 million, albeit remaining low in historical comparison. Furthermore, factoring in the monetary health co-benefits of reducing GHG emissions, all scenarios have a net poverty-alleviating effect. The overall impact on global inequality appears minimal. Nonetheless, inequality decompositions reveal opposing trends in within- and between-country inequality.

Introduction

Meeting the Paris Agreement target of a temperature increase below 2°C would require a significant boost of current policy efforts (Rogelj et al. 2016). Even staying on track with the Nationally Determined Contributions (NDCs) communicated by countries would require changing the current policy trajectory (UNFCCC 2018). Although bringing multiple benefits to the environment, achievement of the stringent global greenhouse gas (GHG) emissions reduction targets is associated with high implementation costs and could

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impact different aspects of human well-being. Moving away from fossil fuels is costly, and the consensus is that mitigation measures would result in lower economic growth and create sizable distributional consequences.

Carbon pricing mechanisms, a proposed solution to reduce GHG emissions, are expected to alter the comparative advantage of nations. Climate change mitigation policies create opportunities for countries and firms that could secure the technical know-how to adapt to a changing production structure. Policies promoting technology-driven decarbonization and penalizing carbon-intensive sectors would adversely affect industries that rely on traditional fossil fuels and – in the absence of compensatory measures- affect workers, firms, and countries exposed to fossil production inputs. Identifying potential winners and losers of such carbon pricing mechanisms is essential to evaluate the political economy considerations during the implementation phase and incorporate compensatory mechanisms. The distributional consequences are country-specific and will be determined by households' sources of income and revenue structure, the reuse of carbon-tax revenues, and the general equilibrium conditions across countries. See Box 1 below for a discussion of the critical factors determining the distributional consequences of carbon pricing policies.

This paper explores the effects of implementing climate-related carbon pricing mechanisms on global poverty and inequality. It links a global computable general equilibrium (CGE) model with a microsimulation framework. The top-down approach links the Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) model with the Global Income Distribution Dynamic (GIDD) microsimulation framework as done by (M. Chepeliev, Osorio-Rodarte, and van der Mensbrugghe 2021). This paper, however, evaluates scenarios that offer a different treatment of the energy generation system in the CGE model. This paper also extends the microsimulation framework in the following ways. First, by expanding the period of analysis from 2035 to 2050; second, by splitting household budget shares into food, energy, and transport components. Lastly, this paper updates the purchasing power parity global poverty lines to estimate global poverty.

Our findings indicate that carbon pricing policies have negative but small poverty and distributional effects, although with heterogeneous effects. This paper presents global poverty trajectories and differences with respect to baseline across time, using different poverty lines and for five carbon pricing scenarios with different levels of ambition. It also presents initial estimates of poverty after accounting for the expected monetary health co-benefits of lowering GHG emissions and measures the impact on between- and within-country inequality.

This paper is organized as follows. The next section presents the methodological framework and underlying data. Then, the CGE global scenarios are presented, analyzing the linkage aggregate variables that will inform the microsimulation. Next, poverty and

Box 1. Key factors that determine the distributional consequences of carbon pricing policies.

First, distributional outcomes significantly depend on income sources and expenditure structure of the households. On the income side, carbon pricing tends to have a more adverse impact on capital earning compared to labor payments (e.g., (Rausch, Metcalf, and Reilly 2011; Dissou and Siddiqui 2014)), therefore households with a higher share of capital income are impacted more adversely. On the expenditure side, distributional impacts highly depend on the share of households' expenditure on energy goods and services. This factor explains why in many low-income countries, where the share of energy expenditures for poor households is much lower than for rich ones, studies find progressive outcomes of carbon pricing (Dorband et al. 2019; Ohlendorf et al. 2021). At the same time, in high income countries, lower income households tend to spend higher share of their income on energy sources compared to the household at the top of the income distribution (e.g. (Hassett, Mathur, and Metcalf 2009; Wier et al. 2005)), which explains regressivity of the observed outcomes.

Second, poverty and distributional outcomes largely depend on the carbon revenue recycling scheme. Studies suggest that using the revenue to lower distortionary taxes has a positive efficiency gain, but higher regressivity, while if the proceeds of the carbon pricing policy are used to raise welfare transfers, this tends to have positive impact on equity (Vandyck and Van Regemorter 2014; Rausch, Metcalf, and Reilly 2011).

Third, general-equilibrium conditions the final distributional outcome. These include consideration of the indirect effects (price adjustments of all goods in the consumption basket), demand-side adjustments of consumers (differentiated demand elasticities between low- and high-income households) and lifetime income proxies (rather than annual household incomes). A meta-analysis performed in (Ohlendorf et al. 2021) suggests that in ex-ante studies, these three study design features tend to increase the likelihood of progressive study outcomes.

distributional results will be showcased. This paper concludes with policy recommendations and explores areas for further research.

Methodology and Data

This section provides an overview of the methodological framework and data used throughout the paper. The first subsection describes the ENVISAGE CGE model from (van der Mensbrugghe 2020). The second subsection presents an overview of the GIDD microsimulation framework from (Bussolo, De Hoyos, and Medvedev 2010; Maliszewska, Osorio-Rodarte, and Gupta 2020), followed by an explanation of the linking of these two models.

ENVISAGE and the TIAM-World energy system model.

(M. Chepeliev et al. 2023) **use a two-model framework to assess energy investment pathways and global carbon pricing mechanisms**. The authors explore the impacts of future mitigation policies by informing the ENVISAGE CGE model with the TIMES Integrated Assessment Model (TIAM-World). Briefly, ENVISAGE consistently treats economic relationships between agents in a global economic system. TIAM-World, as a cost-optimization model, incorporates incentives and constraints into the global energy system.

ENVISAGE is a recursive dynamic and global CGE model with a modular setup. Regarding economic mechanisms, CGE models consistently represent inter-dependencies between all agents operating in different sectors of the economy. The model finds equilibria between supply and demand, resulting in counterfactual quantities and prices for all markets. The ENVISAGE model was calibrated to the Global Trade Analysis Project (GTAP) 10 Power Data Base from (Aguiar et al. 2019; M. Chepeliev 2020b). In addition, the GTAP 10 Power database includes 11 electricity generation technologies and an electricity transmission and distribution activity. The model is complemented with non-CO2 greenhouse gases (GHGs) (M. Chepeliev 2020a) and air pollutant accounts (M. Chepeliev 2021). In the scenarios covered in this paper, the GTAP database was aggregated into 19 regions and 36 sectors[4]. In terms of dynamics, the ENVISAGE model is solved as a sequence of comparative static equilibria where the factors of production accumulate over time up to 2050.

ENVISAGE assumes full-employment equilibria in frictionless labor markets. The ENVISAGE CGE model assumes employment to be a fixed share of a country's working-age population. Labor markets are frictionless, and workers can freely move between activities within specific labor nests. The CGE scenarios analyzed in this paper do not account for adjustment costs and labor market frictions, which have significant short- and long-term consequences. Empirical evidence highlights the importance of adjustment costs due to labor market frictions in molding the distributional consequences of trade (Artuç, Chaudhuri, and McLaren 2010; Autor and Dorn 2013; Dix-Carneiro 2014) and may explain the parallel rise of protectionism and political polarization in recent years (Colantone, Ottaviano, and Stanig 2022). In addition, governments recycle revenue obtained from carbon pricing via a reduction in direct taxes to households unless otherwise specified.

TIMES is a cost-optimization model to explore how the global energy system would respond to different incentives and constraints. It determines the least-cost investment pathway and energy system operation to meet an exogenous demand for energy. It is a flexible and modular framework where energy commodity flows can be customized from primary energy extraction through conversion, production, and end-use. Technologies can be added, removed, or represented at different resolutions. The TIAM-World database is calibrated to the International Energy Agency (IEA) balances of 2019. (M. Chepeliev et al. 2023) provide details on the technological representation of the TIAM-World model. The TIAM-World model was run up to 2100 with carbon budgets (temperature targets) imposed over the 2070 or 2100 timeframes.

[4] See Annex A in (M. Chepeliev et al. 2023)

(M. Chepeliev et al. 2023) **use a soft-linking approach to couple the ENVISAGE and TIAM-World models**. First, the TIAM-World model is run to calibrate the reference scenario and develop a set of mitigation pathways consistent with limiting global warming below 2ºC and 1.5ºC within the 2070 and 2100 timeframe. (M. Chepeliev et al. 2023) develops a reference (or baseline) scenario pathway up to 2050 with no targeted climate actions. On top of the baseline pathway, they impose exploratory mitigation scenarios, including NDCs, a set of more ambitious policy scenarios consistent with limiting global warming at or below 2ºC, as well as a carbon border adjustment mechanism (CBAM) implemented by the European Union. The authors also explore alternative revenue recycling mechanisms within the mitigation scenarios. As a result, they obtained mitigation pathways with varying emission trajectories and carbon budgets from 2019 to 2050. These mitigation pathways are boundary conditions when implementing policy scenarios in the ENVISAGE modeling framework.

The Global Income Distribution Dynamics (GIDD) Model

The GIDD model is used to estimate the poverty and distributional effects of different carbon pricing cooperation arrangements. The GIDD is a top-down macro-micro simulation framework that exploits heterogeneity observed in household surveys to distribute macroeconomic shocks obtained from a model on top, typically a CGE model. GIDD was initiated by (Bussolo, De Hoyos, and Medvedev 2010), inspired by previous efforts involving simulation exercises, such as (Bourguignon, Ferreira, and Leite 2008; Bourguignon, Bussolo, and Pereira da Silva 2008; Davies 2009). As in most top-down modeling frameworks, the CGE drives most behavioral responses. The microsimulation (down) distributes observed changes in a predefined set of linkage aggregate variables that communicate the two models. During the transmission of shocks, a key element is maintaining consistency with observed changes from macro-driven behavior.

The GIDD database contains 125 household surveys with 11.6 million records. It is primarily sourced from World Bank harmonized collections of household budget surveys, such as the World Bank Global Monitoring Database (GMD) and the International Income Distribution Database (I2D2)[5]. These surveys represent 85.9% of the global population (see Table 1). The data is described in more detail in (Ahmed et al. 2020). With respect to regional coverage, the data in GIDD provides consistent coverage for most of the aggregate regions and

[5] The Global Monitoring Database (GMD) is the World Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty and shared prosperity. The household survey data are typically collected by national statistical offices in each country, and then compiled, processed, and harmonized. Additional information on the latest country data can be found in (Castaneda Aguilar et al. 2022). The International Income Distribution Database (I2D2) is a World Bank project to collate, harmonize and make accessible comparable information from household surveys for poverty, inequality, education, demographics, and labor market analysis. For further details on I2D2, see (Montenegro and Hirn 2009).

Table 1. GIDD database coverage and expanded population: 2019, 2030 and 2050

	Microdata	Expanded population					
	Obs	2019		2030		2050	
		millions	%	millions	%	millions	%
East Asia & Pacific	1,010,643	1,978.7	86.3	2,048.9	86.6	1,974.3	86.7
Europe & Central Asia	891,620	801.6	92.1	797.9	91.6	756.2	90.9
Latin America & Caribbean	2,515,162	592.2	92.3	643.3	92.4	680.9	92.6
Middle East & North Africa	690,785	233.0	52.8	271.9	53.8	326.7	55.7
North America	3,679,435	358.2	100.0	381.6	100.0	409.9	100.0
South Asia	954,037	1,744.4	98.0	1,928.3	97.8	2,103.8	97.4
Sub-Saharan Africa	1,880,092	935.1	85.9	1,216.5	86.0	1,845.8	86.5
Total	11,621,774	6,643.2	88.9	7,288.5	88.8	8,097.7	88.6

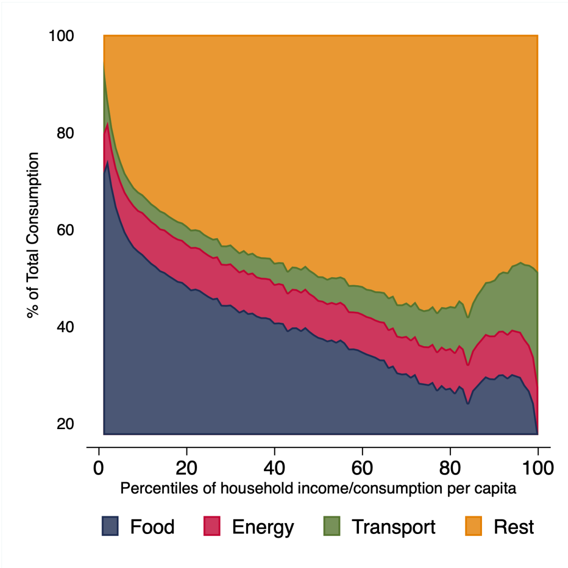
Source: Author's own elaboration.

individual countries, except for the Middle East & North Africa, where only 52.8 percent of the population is represented.

This paper makes several improvements to the GIDD model and data. First, it extends the period of analysis up to 2050. The study done in (M. Chepeliev, Osorio-Rodarte, and van der Mensbrugghe 2021) ended up by 2035. Hence, this paper reweights 125 household surveys to match education and population projections from 2019 up to 2050. The re-weighting process matches the total population in the UN World Population Prospects, disaggregated by 16 age cohorts and gender. In addition, the reweighting allows for an increase in the proportion of skilled labor, defined with a threshold on education greater than 9 years of schooling. Based on each country's demographic trends and initial stock of human capital, the reweighting replicates an increase in the proportion of skilled labor in each country using conservative constant enrollment rates (CER) assumptions. Table 1 shows that, after reweighting, surveys in the GIDD database represent 88.8 and 88.6 percent of the global projected population by 2030 and 2050, respectively.

Second, consumption budget shares are split into food, energy, and travel components. (Maliszewska, Osorio-Rodarte, and Gupta 2020) framework split household consumption into food and non-food consumption. Arguably, this offers a good approximation when there is an interest in the measurement of poverty. Nevertheless, this broad split can hide distributional effects when policies affect other essential consumption items, such as energy and transport, as is the case for carbon pricing schemes. Using microdata from the World Bank's Global Consumption Database (GCD) and following (De Hoyos and Lessem 2008), we estimate global household budget shares for three consumption bundles: food, transport, and energy. The Global Consumption Database provides household-level budget shares for 95 harmonized surveys with a combined sample of 1.17 million households. Since household consumption in the GCD and GIDD databases is expressed in PPP dollars, regressing each budget share as a function of per capita household consumption (in natural logs) is possible – controlling for country-fixed effects.

Figure 1. Estimated household budget shares in the GIDD. Global data



Source: Author's estimation

Econometric estimates are used to predict budget shares across the global distribution of income/consumption. Estimates from the global sample are used to create predicted values for each country in the GIDD database. Figure 1 below summarizes the predicted budget shares for food, energy, transport, and the remaining items using the GIDD database's percentiles of the global income distribution. In accordance with Engel's law, the share of food decreases rapidly when consumption per capita grows, going from 75 percent in the first percentile to 11 percent in the 100th top percentile. Energy's budget follows a U-shaped form, with the bottom 40 percentiles spending, on average, 8.5 percent in energy and the 40th to 80th percentile spending 7.8. Meanwhile, the 80th to 90th percentile spends 8.8 percent of their budget on energy, and the top 10 percent spends 9.3 percent. Lastly, the transport budget share increases as household affluence rises, from 4.1 percent for the bottom 40 percentiles to 6.7 percent in the ten more affluent global percentiles.

Lastly, we update the purchasing power parity global poverty lines. The international poverty estimates presented in this paper used the latest purchasing power parity (PPP) exchange rates to estimate global poverty. With the 2017 PPPs, the *new* extreme poverty line is set at PPP$2.15 a day. Poverty lines of PPP$3.65 and PPP$6.85 a day correspond to countries with lower-middle and upper middle-income status. Updating the PPP has a small effect on the trajectory of global poverty reduction. A detailed discussion can be found in (Jolliffe and Prydz 2021).

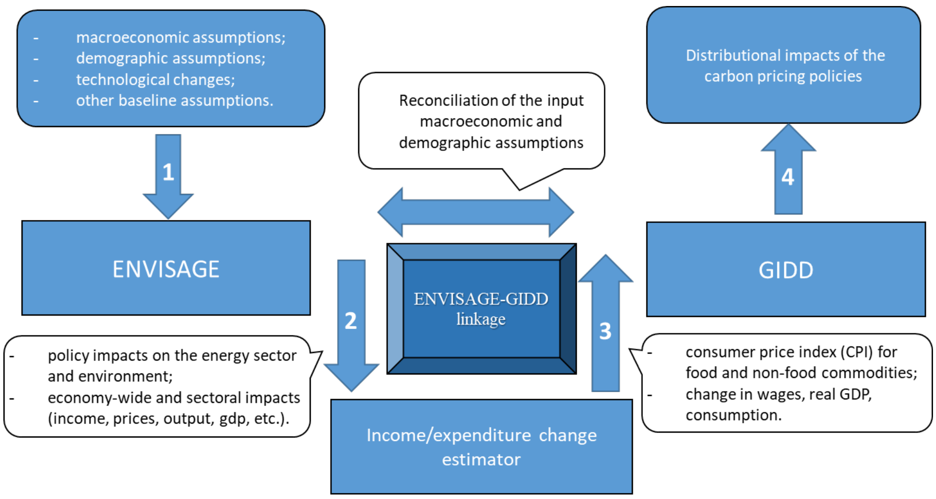
ENVISAGE and GIDD linkage

To provide an assessment of the distributional impacts of carbon taxes, we implement a soft linkage between the ENVISAGE and GIDD models. Figure 2 provides an overview of the general approach. **In the *first step*, we calibrate the baseline scenario for the ENVISAGE model, including the implementation of demographic assumptions**. The same assumptions are used for the calibration of the baseline in the GIDD model. After calibrating the ENIVSAGE baseline path, we implement various carbon pricing policies to estimate policy impacts. These include implications for emission levels, energy output, commodity prices, household income, GDP, wages, final consumption, etc.

In the *second step*, we extract selected output variables reported by the ENVISAGE model and estimate changes in these variables relative to the baseline levels. We further group these variables, as required by the GIDD model. For instance, changes in the consumer price index (CPI) are estimated for food, energy, transport, and the rest of the items; wages are calculated for skilled and unskilled workers in agricultural and non-agricultural sectors.

The third step transmits ENVISAGE outputs to the GIDD model. Prior to this, the GIDD model is calibrated to match the baseline assumptions of the ENVISAGE run demographic profiles. Finally, in the *fourth step*, the GIDD model implements shocks in the selected variables to estimate the distributional impacts of carbon pricing. We discuss *Step Four* in more detail below.

Figure 2. Overview of the ENVISAGE – GIDD linkage.



Source: (M. Chepeliev, Osorio-Rodarte, and van der Mensbrugghe 2021).

GIDD microsimulation

ENVISAGE (macro) and GIDD (micro) models are connected through changes in labor supply, skill formation, real earnings, and household prices. In terms of labor supply, the macro and micro models incorporate projections for skilled and unskilled labor over time. These projections are based on standard population projections provided by the United Nations; in particular, UN medium-variant projection is used (UN DESA 2019). The GIDD framework also reallocates workers across sectors based on aggregate general equilibrium conditions. After reallocation, the GIDD simulates impacts on earnings, income growth, and relative prices for food and non-food expenditures. The shocks are transmitted through linkage aggregate variables that connect macro and micro models.

The first step in the microsimulation exercise is to implement changes in the household surveys' demographic structure. Population growth adjustment is significant in countries with rapid demographic changes. The adjustment for population growth allows the analysis to explicitly consider the changes in the size of the working-age population. The model performs population and education projections during the first stage of the microsimulation run and creates the ENVISAGE model's baseline scenario. For each country, a demographic profile is constructed in two steps. First, the age and gender composition are exogenously determined following medium variant estimates from the World Population Prospects. In the second step, following (Bourguignon and Bussolo 2013), country-specific educational profiles are constructed using initial educational achievement levels observed in the household surveys with some conservative yet simple assumptions about academic progress.

The microsimulations' second step adjusts individual factors returns by skill and sector in accordance with the results of the ENVISAGE model. The GIDD imposes an entirely new vector of earnings for each worker, conditional on each worker's individual characteristics. In a basic setup, the CGE and GIDD can be linked with two sectors (agricultural and non-agricultural) and two types of workers (skilled and unskilled), but depending on the quality of data and the scope of the study, this restriction can be relaxed. The GIDD reallocates workers, moving them out of shrinking and into expanding sectors. The sectoral reallocation process estimates the probability of each worker being reallocated into new sectors based on individual characteristics. Once workers are reallocated, a new vector of earnings is generated using estimates from a set of Mincer equations. To account for unobserved characteristics, each individual residual is brought into the new sectors and scaled accordingly. This later process assures that an individual switching sector can carry his unobservable personal characteristics—beyond age, experience, and years of schooling.

The third step adjusts average wages between groups of workers and sectors. While the second step operates at the individual level, the third step operates at the group level, scaling the average wages for each type of worker and sector. In practical terms, one group is selected as numeraire, i.e., unskilled agricultural, and average wages for each group are scaled relative to the numeraire. Within a group, all earnings are scaled with respect to the numeraire group. Operating through changes in relative wages guarantees internal consistency between macro and micro results, considering that in the ENVISAGE-GIDD linkage, initial relative wages were obtained from the microdata and fed into the global CGE model. It is essential to highlight that until this point, the microsimulation has operated only in relative terms.

Lastly, GIDD adjusts the average income/consumption per capita to guarantee that it changes precisely in line with the ENVISAGE results. After creating new earnings for workers, a vector of per capita household income is constructed considering new earnings and household size. Information about the relationship between income and savings can be incorporated in both micro and macro models. In most circumstances, it is absent in household survey data, as is the case for this paper. A one-to-one passthrough from per capita household income to consumption is assumed in this case. In this regard, the GIDD constructs a household-specific deflator to adjust for changes in relative prices. The price deflator is constructed using initial and final price indexes of food versus non-food expenditure from the macro model and the same household-specific budget consumption shares observed in the micro-data. Food, energy, and transport shares can be adjusted by estimating a Lorenz's curve of budget share expenditure on each item on total per capita household consumption. These GIDD simulation steps are explained in detail in (Maliszewska, Osorio-Rodarte, and Gupta 2020).

GLOBAL SCENARIOS

For the implementation of the baseline scenario, (M. Chepeliev et al. 2023) **calibrate the model to pre-defined GDP and labor force trajectories**. GDP trends are sourced from the International Monetary Fund's (IMF) World Economic Outlook (WEO) (International Monetary Fund 2021). IMF's WEO projections cover the period till 2026. To represent the GDP trends post-2026, (M. Chepeliev et al. 2023) rely on the Shared Socioeconomic Pathways (SSP) database, in particular, the OECD-developed SSP2 scenario (Riahi et al. 2017), which corresponds to the "middle of the road" pathway with intermediate socio-economic challenges for mitigation and adaptation.

To capture the expected energy and emission trends within the baseline scenario, (M. Chepeliev et al. 2023) **incorporate a set of *energy efficiency* assumptions**. These assumptions include declining costs of renewable electricity generation, changes in preferences towards renewables, increases in electricity shares for the final and intermediate consumers, improvements in energy efficiency, increasing share of services and reduction in international transportation costs[6]. Similarly, carbon prices are imposed on a selected set of energy-intensive sectors that correspond to EU emission trading scheme (ETS) activities. The latter include chemicals, metals, non-metallic minerals, petroleum products, wood products and electricity generation[7].

This paper assesses the distributional impacts of five scenarios, each with increasing ambition in carbon reduction goals. Table 2 briefly describes the five policy scenarios evaluated in this paper. The first scenario, NDC, is the least ambitious. Countries comply with their nationally determined contributions (NDCs) and implement carbon pricing

[6] In Annexes D and E, (M. Chepeliev et al. 2023) elaborate on the assumptions used during calibration of their baseline scenario.

[7] (M. Chepeliev et al. 2023) annex E reports corresponding price trajectories.

after 2030. The second scenario, NDC-CBAM, adds the European Union Carbon Border Adjustment Mechanism (CBAM). The CBAM's emission scope and sectoral coverage expand over time. The third scenario contemplates emission reductions consistent with keeping rising temperatures at 2ºC. Lastly, the fourth and fifth scenarios cover mitigation efforts that raise temperatures below 2ºC. The fifth scenario, <2ºC-EARLY, includes an ambitious early climate mitigation action (pre-2030) that sets a global carbon price for achieving more stringent emission reductions compared to the 2ºC scenario.

Table 2. Climate policy scenarios in the ENVISAGE model

Scenario	Description
1. NDC	Includes a translation of unconditional NDCs into regional emission reduction requirements for 2030 relative to the baseline in 2030. Carbon pricing assumptions are applied post-2030.
2. NDC-CBAM	Includes NDC scenario with carbon border adjustment mechanism (CBAM) implemented by the European Union. The emission scope and sectoral coverage of the CBAM is expanding over time.
3. 2°C	Regional-specific emission reduction targets for 2030 based on NDCs and a ramping up of mitigation ambitions post-2030 with a harmonization of global carbon prices consistent with limiting global warming at 2°C.
4. <2°C	Regional-specific emission reduction targets for 2030 based on NDCs and a ramping up of mitigation ambitions post-2030 with a harmonization of global carbon prices consistent with limiting global warming at below 2°C
5. <2°C-EARLY	Includes an ambitious early climate mitigation action (pre-2030) with setting up of a global carbon price, which allows to achieve more stringent emission reductions compared to the 2°C scenario. The climate mitigation target in this scenario is consistent with limiting the increase in global temperature to 1.5°C by 2100.
6. NDC-CO	Follows scenario 1. NDC, and in 2050, accounts for the monetary health-co-benefits of lowering GHG emissions.
7. 2°C-CO	Follows scenario 3. 2°C, and in 2050, accounts for the monetary health-co-benefits of lowering GHG emissions.

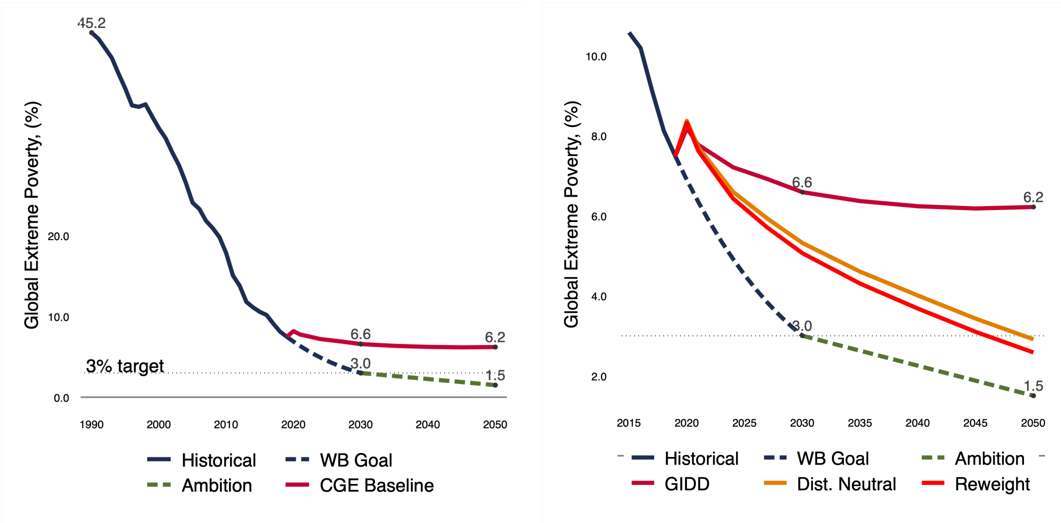
Source: Authors' elaboration based on (M. Chepeliev et al. 2023)

Global Poverty and Distributional Results

In the baseline, global poverty reduction is slow due to low growth and negative distributional consequences. The main driver of poverty reduction is household income/consumption per capita growth. Figure 3 B shows the trajectory of poverty reduction using the GIDD simulation, a distribution-neutral exercise, and an effect on global poverty that uses growth and demographic/education changes. Assuming no change in each country's income distribution, the world would reach the 3 percent global poverty target by 2050 – 20 years after it was promised. Using the full GIDD simulation, the global extreme poverty headcount ratio would decline slowly after the pandemic, reaching 6.6 percent of the global

Figure 3. Global Extreme Poverty, historical and simulations

A. Extreme poverty, 1990 - 2050 B. Extreme poverty, 2015 - 2050



Source: Author's simulations using the ENVISAGE-GIDD model.
Note: Ambition is an author's projection to half extreme poverty to 1.5 percent by 2050. Distribution Neutral does not account for any change in the shape of each country's income distribution, nor any adjustment to the macro to micro growth passthrough. Reweight accounts for the change in the distribution of income that can be attributed to demographic and education projections and the growth effect without growth passthrough adjustment. GIDD includes all simulation steps: reweight, wage premia and sectoral reallocation, adjustment in prices, and growth effect.

population in 2030 and 6.2 percent by 2050[8]. The baseline scenario already incorporates some elements that would reduce global emissions, such as a shift in consumer preferences.

Carbon pricing policies to mitigate emissions hurt global poverty, but even with the more ambitious policy options, the long-term effect is small by historical standards. Figure 4 presents the number of people, in millions, that fall into poverty for scenarios that consider only monetary gains (Pane A) and those that account for health co-benefits (Panel B)[9]. Reducing emissions through carbon instruments yields a negative impact on global poverty. This effect is relatively small when measured using the extreme poverty line of PPP$2.15 a day, going from 5 to 10.3 million depending on the level of ambition by 2050. However, it is more prominent when using the poverty line for upper middle-income countries, at PPP$6.85 per day. In the latter case, poverty could increase between 16.4 and 46.4 million (equivalent to increases in the respective poverty headcount ratio of 0.20 and 0.57 percentage points) depending on the ambition to reach by 2050. More significant increases occur at higher-

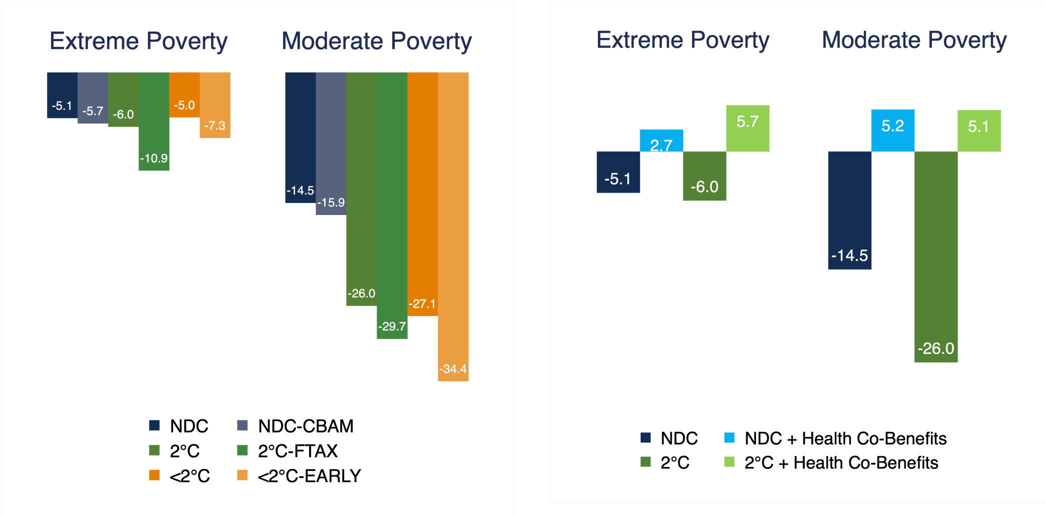
[8] The main switching off the GIDD simulation for India would only decrease the poverty headcount ratio in 0.4 percentage points, from 6.2 to 5.8 percent by 2050.
[9] Table 3 presents the number of people (in millions) that fall into poverty and the corresponding percentage point difference in the global headcount ratio for each scenario and with respect to the baseline.

level poverty lines because, by 2050, a larger share of the population will be located around the upper middle-income poverty line[10].

Figure 4 Poverty reduction by mitigation scenario, with respect to baseline and by 2050, millions of people

A. Scenarios without health co-benefits

B. Scenarios with health co-benefits



Source: Author's simulations using the ENVISAGE-GIDD model.
Note: Extreme and moderate poverty rates are measured with poverty lines of \$2.15 and \$3.65 in PPP(2017)\$ a day, respectively. See the World Bank Poverty and Inequality Platform for additional information (http://pip.worldbank.org)
Note: A positive sign means people lifted from poverty. Negative means people falling below the poverty line.

More ambitious carbon pricing scenarios leave more people in poverty, irrespective of the poverty line; however, the implementation timing matters. The more significant poverty differences with respect to baseline are seen between 2035 and 2040. Table A 1 in the annex shows this by comparing the NDC, 2ºC, and <2ºC-Early scenarios. For instance, by 2030, 2.6 million people would be left in extreme poverty in the NDC scenario, with respect to the baseline. In the 2ºC and <2ºC-Early scenarios, extreme poverty would be higher in a million. In contrast, by 2040, 5.7 million people would fall into extreme poverty under the NDC scenario, while 8.9 and 10.6 million would do the same with the more ambitious 2ºC and <2ºC-Early scenarios, respectively.

The maximum pressure on poverty would be felt in the early stages of implementation, between 2035 and 2040, and for individuals whose per capita income/consumption is around the PPP\$6.85 a day poverty line. The number of people left in poverty could reach up to 59 million under the PPP\$6.85 poverty line between 2035 and 2040 and under the most ambitious <2ºC-Early scenario. This represents an increase of 0.79 percent points in the global poverty headcount ratio with respect to baseline, which could be considered

[10] The effect on poverty is larger when the poverty line is closer to the mode of income distribution. For a discussion on this see (Osorio-Rodarte and Verbeek 2015).

low at the global level and by historical standards. Nevertheless, not all countries are affected equally.

Considering likely co-benefits of lowering GHG emissions would result in nearly 12 million people lifted from poverty under the 2ºC scenario. In this paper, we incorporated the monetary health co-benefits associated with lower air pollutants in two scenarios: NDC and 2ºC following (M. Chepeliev 2021; M. Chepeliev and van der Mensbrugghe 2019). The monetary equivalent of the health co-benefit is calculated ex-post and applied to the entire population, assuming that the monetary equivalent of health co-benefits is distributed evenly across the entire population in each country. Notably, this positive push on the final welfare aggregate would be enough to reduce poverty globally. Figure 4 Pane B shows that accounting for the health co-benefits by 2050 would lift from extreme poverty 7.8 and 11.8 million, with respect to the NDC and 2ºC scenarios. The net impact of the health co-benefits is a reduction between 0.10 and 0.15 in the global extreme poverty headcount ratio (%). The effect is more substantial considering higher poverty lines, particularly at PPP$6.85 a day.

Carbon pricing policies marginally reduce poverty in high and upper-middle-income countries at the expense of increasing poverty in low and lower-middle-income countries. By 2050, 32.2 million would remain in poverty in lower middle-income countries under the 2ºC scenario (0.89 percent of the population in lower middle-income countries), contrasting with a 0.6 million poverty reduction in upper-middle and high-income (or approximately 0.05 percent of the population in these groups). In most scenarios, high-income countries observe minor effects on poverty reduction – poverty reduction is a decline in the difference with respect to baseline, which contrasts with increases in poverty across the board for low and lower middle-income countries. These results suggest that poverty reduction is positively associated with a country's income level, although there is significant heterogeneity within country groupings. Table A 2 in the annex shows the number of people remaining in poverty with respect to baseline by 2050, grouping results by each country's income level per the World Bank definition.

India and Sub-Saharan Africa primarily drive the adverse effects on global poverty. Moreover, a group of countries would see increases in poverty across all carbon pricing scenarios. The adverse global impact on poverty are primarily driven by India, followed by Sub-Saharan Africa[11]. In the NDC scenario, for instance, extreme poverty

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and **Error! Reference source not found.** in Annex 3 show results using the CGE's regional/country aggregation.

shows poverty reduction in millions of people, while **Error! Reference source not found.** shows the percentage point deviation in the poverty headcount.

(PPP$2.15 a day) in India would increase by 3.4 million and 2.0 million in Sub-Saharan Africa, which is equivalent to increases in 0.4 and 0.11 percentage points in India and Sub-Saharan Africa's poverty headcounts. At the higher-level PPP$6.85 poverty line, India's poverty headcount could rise between 0.63 and up to 2.10 percentage points, while Sub-Saharan Africa's poverty headcount ratio would do so between 0.23 and 0.61 p.p. Moreover, among countries that would see adverse effects on poverty across the board are Indonesia, Morocco, the Philippines, the regions Rest of Latin America and the Caribbean, and the Rest of East Asia.

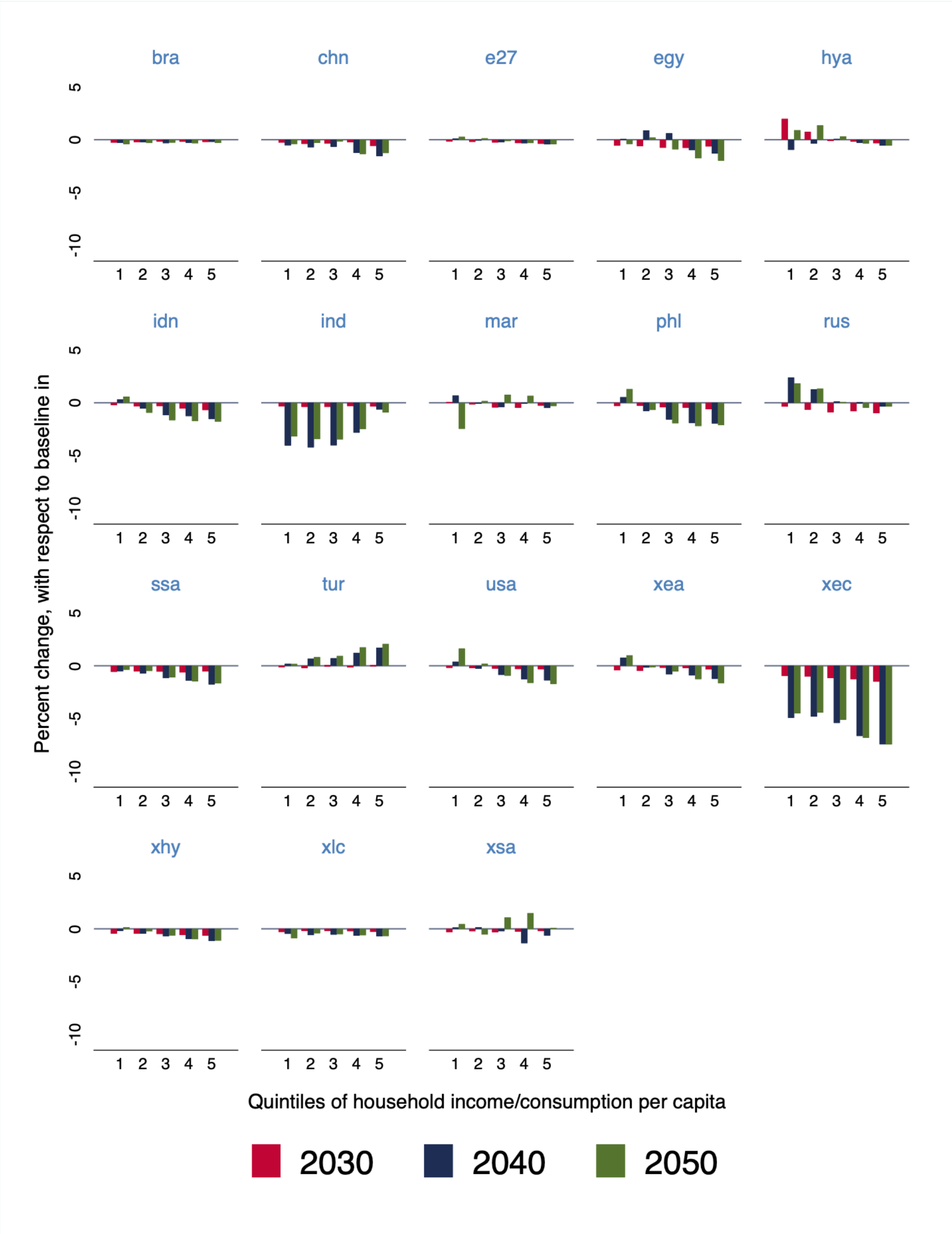
This contrasts with a group of countries that would see gains in poverty reduction across the board. Some countries will observe significant poverty reduction in most climate scenarios, namely China (with a reduction in poverty headcount ratio between 0.2 and 0.9 percentage points), Egypt (between 0.02 and 0.07 percentage points), the United States (between 0.05 and 0.13 p.p.), the Rest of East Asia (between 0.01 and 0.72 p.p.) and the Russian Federation (between 0.03 and 0.09 p.p.). The marked contrast between winners and losers – as shown so far in poverty reduction- may be helpful in assessing alternative compensation mechanisms. Nevertheless, it should be noted that the regional/country groupings used in the CGE can mask within-group heterogeneity, while the net effect may be driven by the most populous country in each region.

Beyond aggregates, carbon pricing mechanisms create winners and losers within countries. Figure 5 and Figure 6 show estimated growth incidence curves for each one of the ENVISAGE aggregate regions with respect to the baseline in 2030, 2040, and 2050. Figure 5 shows the GICs for the 2ºC scenario, while results for the <2ºC-Eearly scenario are shown in Figure 6. In these figures, quintiles of household income/consumption per capita summarize the incidence curves. When the curve lies below the zero line, it means that a quintile is a net loser of the carbon pricing mechanisms. The quintile is a net winner when the curve lies above the zero line. Moreover, when the GICs show a negative slope, we observe a progressive incidence; the burden of carbon prices affects the wealthy in each region. On the contrary, a regressive incidence is observed when the GIC has a positive slope, and hence the gains are concentrated in the wealthier segments of the population. In Turkey and India, results are markedly regressive, indicating that the burden of carbon pricing is imposed on the poor. In particular, the case of India is driven by a significant increase in food prices due to the low availability of land. In contrast, distributional impacts are progressive in most CGE regions (China, the EU27, Egypt, Indonesia, Philippines, the Russian Federation, Sub-Saharan Africa, the United States, the Rest of East Asia, and the Rest of Europe and Central Asia). The impact on each quintile depends on the general equilibrium conditions that determine the demand for labor and each country's skill wage premia, followed by relative prices of food, energy, and transport. Chepeliev et. al. (2023) provide an explanation for these changes.

This paper uses entropy-based inequality indices to summarize changes in inequality between and within countries. Table 3 summarizes the insights of the GICs for the global sample with five inequality measures (a definition of the inequality measures is provided in Annex 1). Inequality indices differ in their sensitivities to income differences in different parts of the distribution. The more positive the 'a' value is, the more sensitive GE(a) is to income differences at the top of the income distribution. GE(0) is the mean logarithmic deviation, GE(1) is the Theil index, and GE(2) is half the square of the coefficient of variation. The Gini coefficient is most sensitive to income differences around the middle (more precisely, the mode). P90/P10 are percentile ratios of the individual in the bottom percentile 90 and in the top 10.

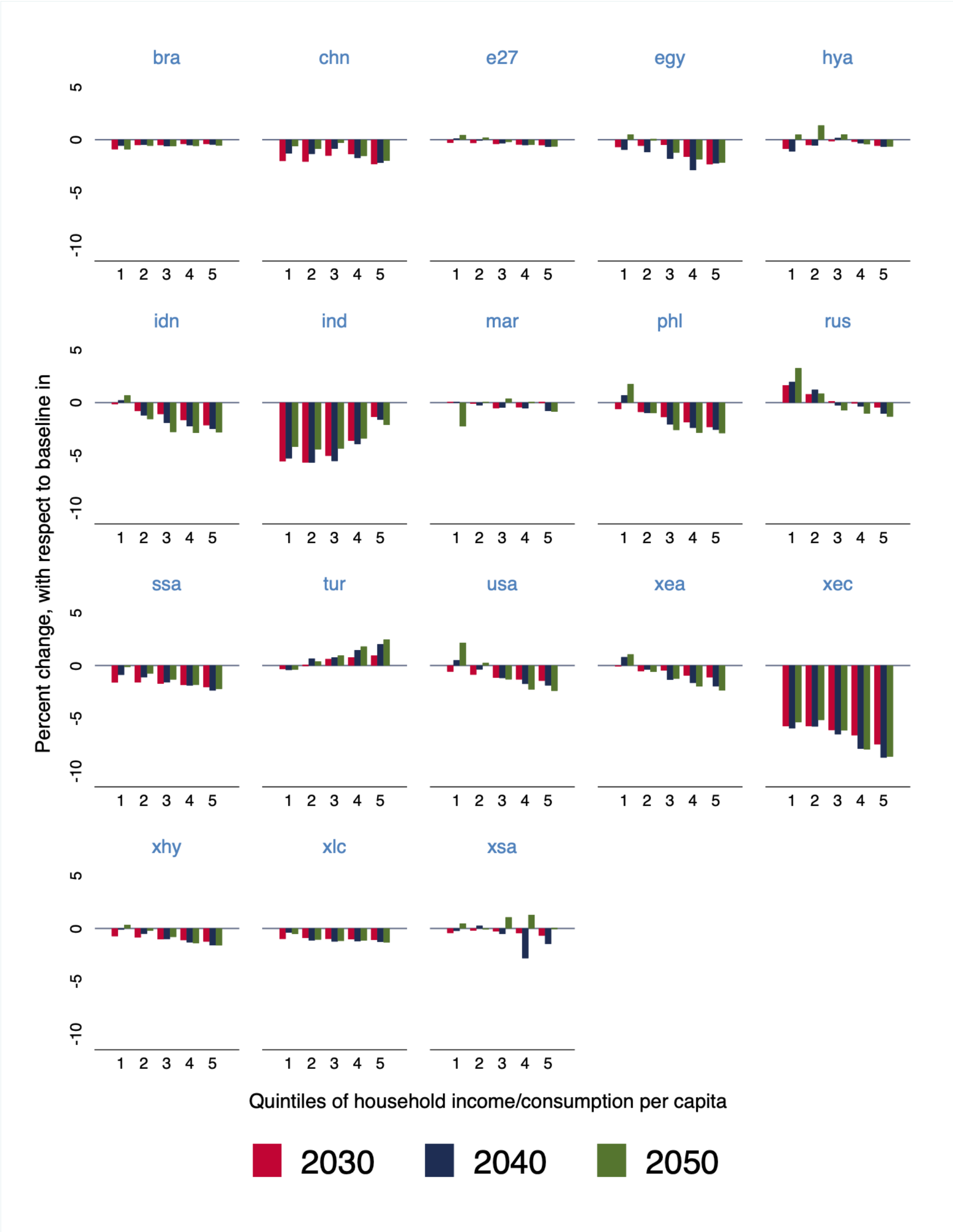
Carbon pricing mechanisms would increase the inequality between countries and reduce within-income inequality. Table 3 shows the initial levels of each of the entropy-based inequality indicators and differences with respect to baseline by 2050 for the NDC, 2ºC, and <2ºC-Early scenarios. Changes in GE(a) indicate increases in inequality when a = 0, and decreases with GE(1) and GE(2). If we put a weight on the bottom of the income distribution, then carbon pricing mechanisms increase global inequality. However, if more weight is given to the middle and upper classes, carbon pricing would have the opposite effect. Moreover, GE(2) differences are higher, indicating that reductions in inequality come from movements of income from top earners, particularly with more ambitious <2ºC-Early scenario. Table 3 also shows that implementation of pricing mechanisms increases the between-country inequality, as the between GE(a) indicator grows for three scenarios, irrespective of the level of a. In contrast, the within-group inequality is reduced in the three instances. The net effect on global inequality is driven by within-country inequality.

Figure 5 Growth Incidence Curves (quintiles) in the 2ºC scenario with respect to baseline, by ENVISAGE region and by 2050



Source: Authors' estimates using ENVISAGE-GIDD Model. Note: bra = Brazil, chn = China, e27 = European Union (27), egy = Egypt, hay = other high income, idn = Indomesia, ind = India, mar = Morocco, phl = Philippines, rus = Russian Federation, ssa = Sub-saharan Africa, tur = Turkeyi, usa = United States, xea = rest of East Asia, xec = Rest of Europe and Central Asia, xhy = Rest of high-income, xlc = Rest of Latin America and the Caribbean, xmn = Rest of Middle East and North Africa, xsa = Rest of South Asia.

Figure 6 Growth Incidence Curves (quintiles) in the <2ºC-Early scenario with respect to baseline, by ENVISAGE region and by 2050



Source: Authors' estimates using ENVISAGE-GIDD Model. Note: bra = Brazil, chn = China, e27 = European Union (27), egy = Egypt, hay = other high income, idn = Indomesia, ind = India, mar = Morocco, phl = Philippines, rus = Russian Federation, ssa = Sub-saharan Africa, tur = Turkeyi, usa = United States, xea = rest of East Asia, xec = Rest of Europe and Central Asia, xhy = Rest of high-income, xlc = Rest of Latin America and the Caribbean, xmn = Rest of Middle East and North Africa, xsa = Rest of South Asia.

Table 3. Global inequality measures and difference to the baseline, by scenario

Inequality Measure	Baseline	NDC	2C	<2C Early	Percentage point difference w.r.t baseline by 2045		
					NDC	2C	<2C-Earl
GE(0)	92.03	92.11	92.20	92.15	0.08	0.18	0.13
GE(1)	88.33	88.27	88.31	88.21	-0.07	-0.03	-0.14
GE(2)	299.96	292.20	298.51	290.50	-2.59	-0.48	-3.15
Between GE(0)	40.93	41.08	41.15	41.25	0.38	0.54	0.79
Between GE(1)	36.40	36.53	36.58	36.68	0.35	0.50	0.78
Between GE(2)	42.72	42.88	42.94	43.08	0.38	0.52	0.83
Within GE(0)	51.11	51.02	51.05	50.91	-0.16	-0.11	-0.40
Within GE(1)	51.93	51.74	51.73	51.53	-0.36	-0.40	-0.79
Within GE(2)	257.24	249.32	255.56	247.42	-3.08	-0.65	-3.82
Gini	66.04	66.05	66.06	66.05	0.01	0.03	0.01
P90P10 Ratio	3352.91	3359.59	3370.84	3359.29	0.20	0.53	0.19

Source: Authors' estimates using ENVISAGE-GIDD Model

CONCLUSIONS

At the intra-regional level, results suggest a higher incidence of poverty in all carbon pricing scenarios, mainly driven by lower economic growth. Carbon pricing mechanisms result in a small but focalized impact on global poverty. Achievement of ambitious targets could result in up to 10 million people living in extreme poverty (below PPP$2.15/day) by 2050; in relative terms, these scenarios correspond to a mild increase in the poverty headcount by 0.06 and 0.13 percentage point difference, respectively. Overall, pricing mechanisms by 2050 increase the between-country components of global inequality. The more ambitious scenarios generally yield more drastic poverty and inequality outcomes. Yet, this can be mitigated once we account for the health co-benefits associated with each scenario.

Our analysis has limitations and needs further extensions. *First,* while representing over 82.7% of the global GDP and 85.4% of the worldwide population, the GIDD database still needs to include some crucial countries explicitly represented in the CGE model, such as Korea, Japan, and Saudi Arabia. Some regions, such as the Middle East and North Africa, have a relatively low representation in GIDD (50% of the population in the case of MENA countries). *Second,* several improvements can be implemented in terms of the ENVISAGE-GIDD model linkage, such as better dynamic inputs from historical micro accounts that could guide macro parameters and behavior. *Third,* both more ambitious and longer-term climate mitigation efforts could be analyzed, i.e., targets consistent with the 1.5ºC pathway and looking forward to 2050-2100. Both these options would probably result in a higher incidence on poverty than those discussed in the paper, though the progressivity of effects could vary. *Fourth,* while focusing on the mid-term time horizon—till 2050, we have not introduced climate change impacts into the general framework. If a longer-term timeframe is considered, considering these interactions would be a critical addition to the implemented framework. *Finally,* within the current assessment, this paper has not explored more questions related to transfer payments and compensations between countries and household groups.

Several studies have reported that the carbon revenue recycling scheme could have significant impact on distributional results (e.g., (Vandyck and Van Regemorter 2014; Goulder et al. 2019)), as well as on macroeconomic impacts in general (e.g. (Freire-González and Ho 2019; Chen et al. 2020)). In this paper, we consider only one carbon revenue recycling option: a lump-sum payment to the representative household within the ENVISAGE modeling framework. This approach to carbon revenue recycling is captured in the GIDD microsimulation model via the uniform shift in the average household income to match the aggregate changes in income reported by the ENVISAGE model. This scaling is performed after other indicators provided by the ENVISAGE model (wages, employment, prices) have been incorporated into the GIDD framework. It should be noted that an assessment of alternative carbon revenue recycling schemes, such as renewable energy subsidy, labor tax adjustments, consumption tax adjustments, etc., is an important research question that could extend results reported in the paper but is beyond the scope of the current study.

The intensity of carbon use within countries remains an important area of research. (Chancel 2022) estimates that "the bottom 50 percent of emitters" in the world population accounted for 12 percent of global emissions in 2019, while the top 10 percent accounted for 48 percent of the total. Lastly, the trajectory of the baseline scenario needs to be addressed. In the current baseline, the World Bank's goal of ending extreme poverty by 2030 has already been postponed 20 years. Accelerating poverty reduction will necessarily make it more difficult to reach the GHG emissions target.

Bibliography

Aguiar, Angel, Maksym Chepeliev, Erwin L. Corong, Robert McDougall, and Dominique van der Mensbrugghe. 2019. "The GTAP Data Base: Version 10." *Journal of Global Economic Analysis* 4 (1): 1–27. https://doi.org/10.21642/jgea.040101af.

Ahmed, S. Amer, Maurizio Bussolo, Marcio Cruz, Delfin S. Go, and Israel Osorio-Rodarte. 2020. "Global Inequality in a More Educated World." *Journal of Economic Inequality* 18: 585–161.

Artuç, Erhan, Shubham Chaudhuri, and John McLaren. 2010. "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review* 100 (3): 1008–45.

Autor, David H, and David Dorn. 2013. "The Growth of Low Skill Service Jobs and the Polarization of the U . S . Labor Market." *American Economic Review* 103 (5): 1553–97. https://doi.org/10.1257/aer.103.5.1553.

Bourguignon, François, and Maurizio Bussolo. 2013. "Income Distribution in Computable General Equilibrium Modeling." In , 1:1383–1437. Handbook of Computable General Equilibrium Modeling. Elsevier. http://ideas.repec.org/h/eee/hacchp/v1y2013icp1383-1437.html.

Bourguignon, François, Maurizio Bussolo, and Luiz A Pereira da Silva. 2008. *The Impact of Macroeconomic Policies on Poverty and Income Distribution : Macro-Micro Evaluation Techniques and Tools*. Houndmills, Basingstoke, Hampshire ; New York Washington, DC: Palgrave Macmillan ; World Bank. http://www.loc.gov/catdir/toc/ecip081/2007040478.html.

Bourguignon, François, Francisco H.G. Ferreira, and Phillippe G. Leite. 2008. "Beyond Oaxaca-Blinder: Accounting for Differences in Household Income Distributions." *Journal of Economic Inequality* 6: 117–48. https://doi.org/10.1007/s10888-007-9063-y.

Bussolo, Maurizio, Rafael E De Hoyos, and Denis Medvedev. 2010. "Economic Growth and Income Distribution: Linking Macro-Economic Models with Household Survey Data at the Global Level." *International Journal of Microsimulation* 3 (1): 92–103. http://ideas.repec.org/a/ijm/journl/v3y2010i1p92-103.html.

Castaneda Aguilar, R. andres, Carolina Diaz-Bonilla, Tony Fujs, Dean Jolliffe, Christoph Lakner, Daniel G. Mahler, Minh C. Nguyen, et al. 2022. "September 2022 Update to the Poverty and Inequality Platform (PIP): What's New."." 24. Global Poverty Monitoring Technical Note Series. Washington, D.C.

Chancel, Lucas. 2022. "Global Carbon Inequality over 1990–2019." *Nature Sustainability* 5 (11). https://doi.org/10.1038/s41893-022-00955-z.

Chen, Jiaqian, Anna Shabunina, James Roaf, Philippe Wingender, Daniel Garcia-Macia, Maksym Chepeliev, Dominique van der Mensbrugghe, and Dora Iakova. 2020. "EU Climate Mitigation Policy." *Departmental Papers* 2020 (013). https://doi.org/10.5089/9781513552569.087.

Chepeliev, Maksym. 2020a. "Development of the Non-CO2 GHG Emissions Database for the GTAP 10A Data Base." *Gtap Research Memoranda* 32.

———. 2020b. "Gtap-Power Data Base: Version 10." *Journal of Global Economic Analysis*. https://doi.org/10.21642/JGEA.050203AF.

———. 2021. "Developing an Air Pollutant Emissions Database for Global Economic Analysis." *Journal of Global Economic Analysis* 6 (2). https://doi.org/10.21642/JGEA.060202AF.

Chepeliev, Maksym, Maryla Maliszewska, Dominique van der Mensbrugghe, and Jin Yuan. 2023. "Climate Mitigation Policies and Restructuring of the Global Value Chains." Mimeo. Washington, D.C.

Chepeliev, Maksym, and Dominique van der Mensbrugghe. 2019. "Global Fossil-Fuel Subsidies and Emission Externalities: Inclusive Approaches to Welfare Assessment." Glasgow, Scotland. https://www.iioa.org/conferences/27th/papers/files/3738.pdf.

Chepeliev, Maksym, Israel Osorio-Rodarte, and Dominique van der Mensbrugghe. 2021. "Distributional Impacts of Carbon Pricing Policies under the Paris Agreement: Inter and Intra-Regional Perspectives." *Energy Economics* 102. https://doi.org/10.1016/j.eneco.2021.105530.

Colantone, Italo, Gianmarco Ottaviano, and Piero Stanig. 2022. "The Backlash of Globalization." In *Handbook of International Economics*, edited by Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, 5:405–77. https://doi.org/10.1016/bs.hesint.2022.02.007.

Davies, James B. 2009. "Combining Microsimulation with CGE and Macro Modelling for Distributional Analysis in Developing and Transition Countries." *International Journal of Microsimulation*, 49–65. https://microsimulation.org/IJM/V2_1/IJM_2_1_4.pdf.

Dissou, Yazid, and Muhammad Shahid Siddiqui. 2014. "Can Carbon Taxes Be Progressive?" *Energy Economics* 42. https://doi.org/10.1016/j.eneco.2013.11.010.

Dix-Carneiro, R. 2014. "Trade Liberalization and Labor Market Dynamics." *Econometrica* 82 (3): 825–85.

Dorband, Ira Irina, Michael Jakob, Matthias Kalkuhl, and Jan Christoph Steckel. 2019. "Poverty and Distributional Effects of Carbon Pricing in Low- and Middle-Income Countries – A Global Comparative Analysis." *World Development* 115. https://doi.org/10.1016/j.worlddev.2018.11.015.

Freire-González, Jaume, and Mun S. Ho. 2019. "Carbon Taxes and the Double Dividend Hypothesis in a Recursive-Dynamic CGE Model for Spain." *Economic Systems Research* 31 (2). https://doi.org/10.1080/09535314.2019.1568969.

Goulder, Lawrence H., Marc A.C. Hafstead, Gyu Rim Kim, and Xianling Long. 2019. "Impacts of a Carbon Tax across US Household Income Groups: What Are the Equity-Efficiency Trade-Offs?" *Journal of Public Economics* 175. https://doi.org/10.1016/j.jpubeco.2019.04.002.

Hassett, Kevin A., Aparna Mathur, and Gilbert E. Metcalf. 2009. "The Incidence of a U.S. Carbon Tax: A Lifetime and Regional Analysis." *Energy Journal* 30 (2). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol30-No2-8.

Hoyos, Rafael De, and Rebecca Lessem. 2008. "Food Shares in Consumption: New Evidence Using Engel Curves for the Developing World," November.

International Monetary Fund. 2021. "World Economic Outlook Update, January 2021." *World Economic Outlook*, no. January 2021.

Jolliffe, Dean, and Espen Beer Prydz. 2021. "Societal Poverty: A Relative and Relevant Measure." *World Bank Economic Review* 35 (1). https://doi.org/10.1093/wber/lhz018.

Maliszewska, Maryla, Israel Osorio-Rodarte, and Rakesh Gupta. 2020. "ExAnte Evaluation of Sub National Labor Market Impacts of Trade Reforms." No. 9478. Policy Research Working Paper. Washington D.C. https://openknowledge.worldbank.org/handle/10986/34833.

Mensbrugghe, Dominique van der. 2020. "The Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) Model, Version 10.1." TP/19/01. GTAP Technical Paper.

Montenegro, Claudio, and Maximilian L. Hirn. 2009. "A New Disaggregated Set of Labor Market Indicators Using Standardized Household Surveys from Around the World." World Development Report Background Papers. https://openknowledge.worldbank.org/handle/10986/9033.

Ohlendorf, Nils, Michael Jakob, Jan Christoph Minx, Carsten Schröder, and Jan Christoph Steckel. 2021. "Distributional Impacts of Carbon Pricing: A Meta-Analysis." *Environmental and Resource Economics* 78 (1). https://doi.org/10.1007/s10640-020-00521-1.

Osorio-Rodarte, Israel, and Jos Verbeek. 2015. "How Effective Is Growth for Poverty Reduction? Do All Countries Benefit Equally from Growth?" Let's Talk Development. 2015. http://blogs.worldbank.org/developmenttalk/how-effective-growth-poverty-reduction-do-all-countries-benefit-equally-growth.

Peters, Jeffrey C. 2016a. "GTAP-E-Power: An Electricity-Detailed Economy-Wide Model." *Journal of Global Economic Analysis* 1 (2). https://doi.org/10.21642/JGEA.010204AF.

———. 2016b. "The GTAP-Power Data Base: Disaggregating the Electricity Sector in the GTAP Data Base." *Journal of Global Economic Analysis* 1 (1). https://doi.org/10.21642/JGEA.010104AF.

Rausch, Sebastian, Gilbert E. Metcalf, and John M. Reilly. 2011. "Distributional Impacts of Carbon Pricing: A General Equilibrium Approach with Micro-Data for Households." *Energy Economics* 33 (SUPPL. 1). https://doi.org/10.1016/j.eneco.2011.07.023.

Riahi, Keywan, Detlef P. van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C. O'Neill, Shinichiro Fujimori, Nico Bauer, et al. 2017. "The Shared Socioeconomic Pathways and

Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview." *Global Environmental Change* 42: 153–68. https://doi.org/10.1016/j.gloenvcha.2016.05.009.

Rogelj, Joeri, Michel Den Elzen, Niklas Höhne, Taryn Fransen, Hanna Fekete, Harald Winkler, Roberto Schaeffer, Fu Sha, Keywan Riahi, and Malte Meinshausen. 2016. "Paris Agreement Climate Proposals Need a Boost to Keep Warming Well below 2 °c." *Nature*. https://doi.org/10.1038/nature18307.

UN DESA. 2019. *World Population Prospects 2019. United Nations. Department of Economic and Social Affairs. World Population Prospects 2019.* http://www.ncbi.nlm.nih.gov/pubmed/12283219.

UNFCCC. 2018. "Paris Agreement - Status of Ratification." 21st Conference of the Parties. 2018.

Vandyck, Toon, and Denise Van Regemorter. 2014. "Distributional and Regional Economic Impact of Energy Taxes in Belgium." *Energy Policy* 72. https://doi.org/10.1016/j.enpol.2014.04.004.

Wier, Mette, Katja Birr-Pedersen, Henrik Klinge Jacobsen, and Jacob Klok. 2005. "Are CO2 Taxes Regressive? Evidence from the Danish Experience." *Ecological Economics* 52 (2). https://doi.org/10.1016/j.ecolecon.2004.08.005.

ANNEX 1: OVERVIEW OF THE SELECTED INEQUALITY MEASURES

Consider a population of persons (or households), $i = 1,...,n$, with income y_i, and weight w_i. Let $f_i = w_i / N$, where $N = \sum w_i$. In what follows all sums ($\sum$) are over all values of whatever is subscripted. When the data are unweighted, $w_i = 1$ and $N = n$. Arithmetic mean income is m. Suppose there is an exhaustive partition of the population into mutually-exclusive subgroups $k = 1,...,K$.

Then ***Generalized Entropy class of inequality indices*** is given by:

$$GE(a) = [1 / (a (a - 1)] \{[\sum f_i (y_i / m)^a] - 1 \}, a \mathrel{!=} 0 \text{ and } a \mathrel{!=} 1,$$

$$GE(1) = SUM\, f_i (y_i / m) \log(y_i / m),$$

$$GE(0) = SUM\, f_i \log(m / y_i).$$

Each GE(a) index can be additively decomposed as

$$GE(a) = GE\_W(a) + GE\_B(a),$$

where $GE\_W(a)$ is ***within-group inequality*** and $GE\_B(a)$ is ***between-group inequality*** and

$$GE\_W(a) = \sum [v_k^{(1-a)}] * [s_k^a] * GE_k(a),$$

where $v_k = N_k / N$ is the number of persons in subgroup k divided by the total number of persons (subgroup population share), and s_k is the share of total income held by k's members (subgroup income share). Strictly speaking, v_k is the sum of the weights in subgroup k divided by the sum of the weights for the full estimation sample.

$GE_k(a)$, inequality for subgroup k, is calculated as if the subgroup were a separate population, and $GE\_B(a)$ is derived assuming every person within a given subgroup k received k's mean income, m_k.

The ***Gini coefficient*** is given by:

$$G = 1 + (1 / N) - [2/(m * N^2)] [\sum (N - i + 1) y_i],$$

where persons are ranked in ascending order of y_i. The Gini coefficient (and the percentile ratios) cannot be written as the sum of a term summarizing within-group inequality and a term summarizing between-group inequality.

ANNEX 2: THE ENVISAGE MODEL

The Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) Model (van der Mensbrugghe 2020), at its core, is a recursive dynamic and global CGE model. It follows the circular flow of an economic paradigm. Firms purchase input factors (for example, labor and capital) to produce goods and services. Households receive the factor income and, in turn, demand the goods and services produced by firms. Equality of supply and demand determines equilibrium prices for factors, goods, and services. The model is solved as a sequence of comparative static equilibria where the factors of production are linked between time periods with accumulation expressions. Production is implemented as a series of nested constant-elasticity-of-substitution (CES) functions to capture the substitutability across all inputs. Production is also identified by vintage – divided into *Old* and *New*—with typically lower substitution possibilities associated with *Old* capital.

Income accrues from payments to factors of production and is allocated to households (after taxes). The government sector accrues all net tax payments and purchases goods and services. The model incorporates multiple utility functions for determining household demand—for this paper, the constant-differences-in-elasticities (CDE) utility function was chosen. Trade is modeled using the so-called Armington specification that posits that demand for goods are differentiated by region of origin. The model allows for domestic/import sourcing at the aggregate level (after aggregating domestic absorption across all agents), or at the agent-level.

The model has two fundamental markets for goods and services. Domestically produced goods sold on the domestic market, and domestically produced goods sold by region of destination. All other goods and services are composite bundles of these goods. Two market equilibrium conditions are needed to clear these two markets.

The model incorporates five types of production factors: 1) labor (of which there can be up to five types); 2) capital; 3) land; 4) a sector-specific natural resource (such as fossil fuel energy reserves); and 5) (optionally) water. The labor market is allowed to be segmented (though not required). The model allows for regime switching between full and partial wage flexibility. Capital is allocated across sectors so as to equalize rates of returns. If all sectors are expanding, *Old* capital is assumed to receive the economy-wide rate of return. The old capital is sold on secondary markets in contracting sectors using an upward-sloping supply curve.

ENVISAGE incorporates the main greenhouse gases—carbon, methane, nitrous oxides and fluorinated gases, though in the current study we focus only on CO_2 emissions from fossil fuels combustion. A number of carbon control regimes are available in the model. The incidence of the carbon tax allows for partial or full exemption by commodity and end-user. The model allows for emission caps in a flexible manner—where regions/sectors can be segmented into coalitions.

Dynamics involves three elements. Labor supply (by skill level) grows at an exogenously determined rate. The aggregate capital supply evolves according to the standard stock/flow motion equation, i.e. the capital stock at the beginning of each period is equal to the previous period's capital stock, less depreciation, plus the previous period's level of investment. The third element is technological change. The standard version of the model assumes labor augmenting technical change—calibrated to given assumptions about GDP growth and inter-sectoral productivity differences. Overview of the key nesting structures and elasticity values of the model are provided in Appendix A. Detailed documentation of the ENVISAGE model is provided in (van der Mensbrugghe 2020).

For the purposes of this study, the most important parameters are the inter-fuel substitution elasticities and in particular the substitution elasticity across different power generation technologies. For this study, we applied a relatively modest value of the power substitution elasticity of 1.2.[12]

The ENVISAGE model used in this study is calibrated to the Global Trade Analysis Project (GTAP) 9.2 Power Data Base with 2011 reference year, which distinguishes 141 regions and 65 sectors (Peters 2016b). The latter includes 11 electricity generation technologies, as well as an electricity transmission and distribution activity. For the purposes of this paper, (M. Chepeliev et al. 2023) use an aggregation that includes 28 regions and 29 sectors.

[12] These elasticity values are consistent with estimates reported in (Peters 2016a).

ANNEX 3: ADDITIONAL SIMULATION RESULTS

Table A 1. Poverty with respect to baseline, by scenario and poverty line

Poverty line	Scenario	Change in Poverty, millions					Change in Headcount, p.p.				
		2030	2035	2040	2045	2050	2030	2035	2040	2045	2050
PPP$2.15	NDC	3.9	7.1	6.2	5.7	5.1	0.05	0.09	0.08	0.07	0.06
	NDC-CBAM	4.5	7.6	7.2	6.4	5.7	0.06	0.10	0.09	0.08	0.07
	2°C	4.1	14.5	11.3	8.6	6.0	0.06	0.19	0.15	0.11	0.07
	2°C-FTAX	4.0	16.9	14.3	11.8	10.9	0.06	0.22	0.19	0.15	0.14
	<2°C	4.1	14.5	11.2	8.5	5.0	0.06	0.19	0.14	0.11	0.06
	<2°C-EARLY	23.1	17.7	13.7	10.8	7.3	0.32	0.24	0.18	0.14	0.09
	NDC-CO					-2.7					-0.03
	2°C-CO					-5.7					-0.07
PPP$3.65	NDC	6.8	17.3	14.6	14.7	14.5	0.09	0.23	0.19	0.18	0.18
	NDC-CBAM	7.7	18.2	16.3	16.6	15.9	0.11	0.24	0.21	0.21	0.20
	2°C	7.3	43.3	33.6	28.3	26.0	0.10	0.58	0.43	0.36	0.32
	2°C-FTAX	8.7	48.2	38.3	31.2	29.7	0.12	0.64	0.49	0.39	0.37
	<2°C	7.3	43.3	34.5	30.0	27.1	0.10	0.58	0.45	0.38	0.34
	<2°C-EARLY	59.9	57.8	45.3	38.2	34.4	0.82	0.77	0.58	0.48	0.42
	NDC-CO					-5.2	0.09	0.23	0.19	0.19	-0.06
	2°C-CO					-5.1	0.10	0.57	0.43	0.36	-0.06
PPP$6.85	NDC	8.1	20.4	18.8	18.9	19.5	0.11	0.27	0.24	0.24	0.24
	NDC-CBAM	9.2	21.2	20.2	20.4	21.3	0.13	0.28	0.26	0.26	0.26
	2°C	8.8	45.6	42.8	38.6	34.7	0.12	0.61	0.55	0.49	0.43
	2°C-FTAX	10.5	52.6	46.2	38.2	33.2	0.14	0.70	0.60	0.48	0.41
	<2°C	8.8	45.6	44.0	41.5	38.8	0.12	0.61	0.57	0.52	0.48
	<2°C-EARLY	52.0	59.9	58.6	55.3	48.0	0.71	0.80	0.76	0.70	0.59
	NDC-CO					-8.7					-0.11
	2°C-CO					-5.5					-0.07
PPP$10.00	NDC	7.2	15.3	16.6	16.0	16.1	0.10	0.20	0.21	0.20	0.20
	NDC-CBAM	8.2	15.9	17.9	17.5	17.9	0.11	0.21	0.23	0.22	0.22
	2°C	7.6	32.9	32.2	30.2	28.3	0.10	0.44	0.42	0.38	0.35
	2°C-FTAX	9.2	40.8	33.9	28.5	24.7	0.13	0.54	0.44	0.36	0.30
	<2°C	7.6	32.9	33.1	32.6	32.2	0.10	0.44	0.43	0.41	0.40
	<2°C-EARLY	39.5	46.4	47.0	43.1	40.0	0.54	0.62	0.61	0.54	0.49
	NDC-CO					-5.2					-0.06
	2°C-CO					-4.6					-0.06
PPP$20.00	NDC	6.7	8.3	11.3	11.7	11.4	0.09	0.11	0.15	0.15	0.14
	NDC-CBAM	8.4	8.8	12.1	13.5	13.4	0.12	0.12	0.16	0.17	0.17
	2°C	6.4	15.2	19.2	21.1	21.0	0.09	0.20	0.25	0.27	0.26
	2°C-FTAX	7.9	23.0	23.6	21.7	18.5	0.11	0.31	0.30	0.27	0.23
	<2°C	6.4	15.3	18.9	23.8	23.4	0.09	0.20	0.24	0.30	0.29
	<2°C-EARLY	25.2	24.5	27.8	37.1	31.2	0.35	0.33	0.36	0.47	0.39
	NDC-CO					-7.0					-0.09
	2°C-CO					-8.9					-0.11

Source: Author's simulation using the ENVISAGE-GIDD model.

Table A 2. Poverty with respect to baseline in 2050, by income and poverty line

Poverty line	Scenario	Change in Poverty, millions					Change in Headcount, p.p.				
		LIC	LMI	UMI	HIC	ALL	LIC	LMI	UMI	HIC	All
PPP$2.15	NDC	1.5	3.5	0.1	0.0	5.1	0.16	0.09	0.01	0.00	0.06
	NDC-CBAM	1.7	3.8	0.2	0.0	5.7	0.19	0.10	0.01	0.00	0.07
	2°C	-0.2	6.3	0.1	-0.1	6.0	-0.02	0.16	0.00	-0.01	0.07
	2°C-FTAX	0.4	10.2	0.5	-0.1	10.9	0.04	0.26	0.02	-0.01	0.14
	<2°C	-1.0	6.1	0.1	-0.2	5.0	-0.11	0.16	0.00	-0.02	0.06
	<2°C-EARLY	-0.1	7.4	0.1	-0.1	7.3	-0.01	0.19	0.00	-0.02	0.09
	NDC-CO	-0.5	-1.9	-0.2	-0.1	-2.7	-0.06	-0.05	-0.01	-0.01	-0.03
	2°C-CO	-2.2	-3.2	-0.2	-0.2	-5.7	-0.25	-0.08	-0.01	-0.02	-0.07
PPP$3.65	NDC	2.5	12.0	0.1	0.0	14.5	0.28	0.30	0.00	0.00	0.18
	NDC-CBAM	2.9	12.8	0.1	0.0	15.9	0.32	0.33	0.01	0.00	0.20
	2°C	2.1	24.4	-0.3	-0.2	26.0	0.23	0.62	-0.01	-0.02	0.32
	2°C-FTAX	1.0	28.3	0.5	-0.1	29.7	0.11	0.72	0.02	-0.01	0.37
	<2°C	2.1	25.4	-0.1	-0.2	27.1	0.23	0.65	-0.01	-0.03	0.34
	<2°C-EARLY	3.0	31.7	-0.1	-0.3	34.4	0.33	0.81	0.00	-0.03	0.42
	NDC-CO	0.3	-4.8	-0.5	-0.2	-5.2	0.03	-0.12	-0.02	-0.02	-0.06
	2°C-CO	0.3	-4.5	-0.7	-0.2	-5.1	0.04	-0.12	-0.03	-0.02	-0.06
PPP$6.85	NDC	2.4	17.4	0.0	-0.2	19.5	0.26	0.44	0.00	-0.03	0.24
	NDC-CBAM	2.7	18.6	0.2	-0.2	21.3	0.29	0.47	0.01	-0.02	0.26
	2°C	2.8	32.3	0.0	-0.5	34.7	0.30	0.82	0.00	-0.05	0.43
	2°C-FTAX	1.5	30.4	1.6	-0.3	33.2	0.16	0.77	0.07	-0.04	0.41
	<2°C	3.2	35.7	0.3	-0.4	38.8	0.35	0.91	0.01	-0.05	0.48
	<2°C-EARLY	4.1	43.6	0.8	-0.4	48.0	0.45	1.11	0.03	-0.05	0.59
	NDC-CO	0.5	-7.7	-1.1	-0.4	-8.7	0.06	-0.20	-0.05	-0.04	-0.11
	2°C-CO	1.5	-5.2	-1.2	-0.6	-5.5	0.16	-0.13	-0.05	-0.06	-0.07
PPP$10.00	NDC	1.3	13.9	0.9	-0.1	16.1	0.15	0.36	0.04	-0.01	0.20
	NDC-CBAM	1.6	15.2	1.1	0.0	17.9	0.18	0.39	0.05	0.00	0.22
	2°C	2.0	24.7	2.0	-0.4	28.3	0.22	0.63	0.09	-0.04	0.35
	2°C-FTAX	0.9	21.2	3.0	-0.4	24.7	0.10	0.54	0.13	-0.05	0.30
	<2°C	2.3	28.2	2.4	-0.7	32.2	0.25	0.72	0.10	-0.08	0.40
	<2°C-EARLY	3.2	33.4	4.0	-0.7	40.0	0.36	0.85	0.17	-0.08	0.49
	NDC-CO	0.5	-3.7	-1.3	-0.6	-5.2	0.05	-0.10	-0.06	-0.06	-0.06
	2°C-CO	1.0	-3.3	-1.5	-0.8	-4.6	0.11	-0.08	-0.06	-0.09	-0.06
PPP$20.00	NDC	1.0	7.7	3.2	-0.5	11.4	0.10	0.20	0.14	-0.05	0.14
	NDC-CBAM	1.1	7.9	4.5	0.0	13.4	0.12	0.20	0.19	0.00	0.17
	2°C	1.6	13.5	7.0	-1.1	21.0	0.17	0.34	0.30	-0.13	0.26
	2°C-FTAX	0.9	11.2	7.4	-1.1	18.5	0.10	0.29	0.31	-0.12	0.23
	<2°C	1.9	15.5	7.7	-1.7	23.4	0.21	0.39	0.33	-0.19	0.29
	<2°C-EARLY	2.1	21.1	9.7	-1.6	31.2	0.24	0.54	0.41	-0.18	0.39
	NDC-CO	0.3	-4.4	-1.7	-1.2	-7.0	0.03	-0.11	-0.07	-0.13	-0.09
	2°C-CO	1.1	-5.8	-2.1	-2.0	-8.9	0.12	-0.15	-0.09	-0.22	-0.11

Source: Authors' estimates using ENVISAGE-GIDD Model.

Note: LIC = low-income. LMI = lower middle-income. UMI = upper middle-income. HIC = high income.

Table A 3. Poverty with respect to baseline in 2050, by ENVISAGE region and poverty line

Scenario	Code	Poverty line, PPP(2011)$					Code	Poverty line, PPP(2011)$				
		$2.15	$3.65	$6.85	$10.00	$20.00		$2.15	$3.65	$6.85	$10.00	$20.00
NDC	bra	0.0	0.0	0.1	0.1	0.0	ssa	2.1	4.5	4.3	3.6	2.8
NDC-CBAM		0.0	0.1	0.1	0.1	0.0		2.2	4.9	4.8	4.1	3.0
2°C		0.0	0.0	0.1	0.1	0.1		2.0	7.1	7.4	6.6	5.2
2°C-FTAX		0.0	0.1	0.4	0.4	0.1		5.0	7.9	5.4	4.0	3.1
<2°C		0.0	0.1	0.2	0.2	0.2		1.0	6.9	8.3	7.6	6.3
<2°C-EARLY		0.0	0.1	0.2	0.2	-0.2		1.8	9.2	10.1	9.5	7.2
NDC-CO		0.0	0.0	0.0	-0.2	-0.2		-0.7	0.5	1.0	1.5	1.0
2°C-CO		0.0	0.0	0.1	-0.1	0.0		-0.8	3.4	4.8	4.3	3.9
NDC	chn	0.0	0.0	0.1	0.4	2.4	tur	0.0	0.0	0.0	0.0	-0.1
NDC-CBAM		0.0	0.0	0.1	0.7	3.4		0.0	0.0	0.0	0.0	-0.1
2°C		0.0	-0.2	0.0	1.2	5.4		0.0	-0.1	0.0	0.0	-0.1
2°C-FTAX		0.0	-0.2	0.0	1.1	5.5		0.0	0.0	0.2	0.1	-0.1
<2°C		0.0	-0.3	0.0	1.1	5.6		0.0	0.0	0.0	0.0	-0.1
<2°C-EARLY		0.0	-0.3	0.1	2.1	7.1		0.0	0.0	0.1	0.0	0.0
NDC-CO		0.0	-0.2	-0.3	-0.5	-1.0		0.0	-0.1	0.0	-0.2	-0.4
2°C-CO		-0.1	-0.3	-0.4	-1.0	-2.0		0.0	-0.1	0.0	-0.2	-0.5
NDC	e27	0.0	0.0	0.0	0.0	-0.1	usa	0.0	0.0	-0.2	-0.1	-0.3
NDC-CBAM		0.0	0.0	0.0	0.1	0.1		0.0	0.0	-0.2	-0.1	-0.1
2°C		0.0	0.0	0.1	0.0	-0.1		-0.1	-0.2	-0.5	-0.3	-0.9
2°C-FTAX		0.0	0.1	0.1	0.2	0.4		-0.1	-0.2	-0.4	-0.5	-1.4
<2°C		0.0	0.0	0.1	0.0	-0.1		-0.1	-0.2	-0.4	-0.6	-1.3
<2°C-EARLY		0.0	0.0	0.1	0.1	-0.1		-0.1	-0.2	-0.5	-0.6	-1.3
NDC-CO		0.0	0.0	0.0	-0.1	-0.4		0.0	-0.1	-0.3	-0.4	-0.6
2°C-CO		0.0	0.0	0.0	0.0	-0.2		-0.1	-0.2	-0.6	-0.6	-1.5
NDC	egy	0.0	0.0	0.2	0.2	0.4	xea	0.0	-0.1	-0.5	-0.1	0.4
NDC-CBAM		0.0	0.0	0.2	0.3	0.4		0.0	-0.1	-0.3	0.0	0.4
2°C		0.0	0.1	0.2	0.2	0.7		0.0	-0.4	-1.2	-0.2	0.7
2°C-FTAX		0.1	0.2	0.5	0.5	0.4		0.0	0.0	-0.1	0.4	0.9
<2°C		0.0	0.1	0.2	0.3	0.9		0.0	-0.4	-1.2	-0.2	0.7
<2°C-EARLY		0.0	0.1	0.3	0.3	0.9		0.0	-0.4	-1.2	-0.1	1.1
NDC-CO		0.0	0.0	0.0	0.2	0.3		0.0	-0.1	-0.8	-0.6	-0.2
2°C-CO		0.0	0.0	0.0	0.0	0.5		0.0	-0.5	-1.6	-0.7	-0.2
NDC	hya	0.1	0.0	0.0	0.0	0.0	xec	0.0	0.2	0.4	0.6	0.9
NDC-CBAM		0.0	0.0	0.0	0.0	0.0		0.0	0.2	0.4	0.6	1.0
2°C		0.1	0.1	0.0	0.0	0.0		0.1	0.3	0.9	1.4	2.2
2°C-FTAX		0.1	0.1	0.0	0.0	0.0		0.1	0.6	1.3	2.2	2.9
<2°C		0.1	0.4	0.2	0.0	0.0		0.1	0.4	1.1	1.6	2.4
<2°C-EARLY		0.1	0.1	0.0	0.0	0.0		0.1	0.4	1.2	1.7	2.6
NDC-CO		0.0	-0.1	0.0	0.0	0.0		0.0	0.2	0.4	0.5	0.9
2°C-CO		0.0	0.0	0.0	0.0	0.0		0.1	0.3	0.9	1.3	2.1

Source: Author's simulation using the ENVISAGE-GIDD model.

Table A 4. Change in poverty with respect to baseline in 2050, by income level and poverty line (cont.)

Scenario	Code	Poverty line, PPP(2011)$					Code	Poverty line, PPP(2011)$				
		$2.15	$3.65	$6.85	$10.00	$20.00		$2.15	$3.65	$6.85	$10.00	$20.00
NDC	idn	-0.1	-0.1	0.3	0.4	0.5	xhy	0.0	0.0	0.0	0.0	0.0
NDC-CBAM		-0.1	-0.1	0.3	0.5	0.5		0.0	0.0	0.0	0.0	0.1
2°C		-0.3	-0.3	0.8	1.1	1.3		0.0	0.0	0.0	0.0	0.0
2°C-FTAX		0.9	1.2	0.9	0.2	1.1		0.0	0.0	0.0	0.0	0.1
<2°C		-0.4	-0.5	0.9	1.2	1.7		0.0	0.0	0.0	0.0	-0.1
<2°C-EARLY		-0.4	-0.4	1.5	1.9	2.5		0.0	0.0	0.0	0.0	-0.1
NDC-CO		-0.3	-0.5	-0.6	-0.9	-0.6		0.0	0.0	0.0	0.0	-0.1
2°C-CO		-0.4	-0.5	0.1	0.1	0.6		0.0	0.0	0.0	0.0	-0.1
NDC	ind	3.0	9.6	13.8	9.5	2.5	xlc	0.0	0.1	0.1	0.3	0.2
NDC-CBAM		3.2	10.3	14.4	10.2	2.5		0.0	0.1	0.2	0.3	0.4
2°C		6.3	21.2	26.5	17.7	4.8		0.0	0.1	0.3	0.8	1.0
2°C-FTAX		6.9	21.2	23.7	14.8	4.3		0.1	0.2	0.6	0.8	0.8
<2°C		6.8	22.8	29.4	19.5	5.0		0.0	0.1	0.5	1.1	1.5
<2°C-EARLY		7.9	27.3	35.3	22.9	8.1		0.0	0.3	0.8	1.5	2.0
NDC-CO		-0.8	-3.5	-6.2	-3.0	-5.0		-0.1	-0.2	-0.4	-0.5	-0.6
2°C-CO		-1.2	-3.1	-4.7	-3.7	-9.8		-0.1	-0.1	-0.2	0.1	0.2
NDC	mar	0.0	0.0	0.0	0.0	0.1	xmn	0.0	0.1	0.1	0.1	0.1
NDC-CBAM		0.0	0.0	0.0	0.0	0.1		0.2	0.3	0.2	0.3	0.1
2°C		0.0	-0.1	-0.2	-0.1	0.1		-1.6	-1.6	-0.9	-0.7	-0.7
2°C-FTAX		0.0	0.0	-0.1	0.0	0.1		-2.3	-2.2	-1.0	-0.7	-0.7
<2°C		0.0	-0.1	-0.2	-0.1	0.1		-2.0	-1.8	-1.1	-0.9	-0.8
<2°C-EARLY		0.0	-0.1	-0.1	-0.1	0.2		-1.8	-1.6	-0.9	-0.7	-0.7
NDC-CO		0.0	0.0	-0.1	-0.1	0.0		-0.2	-0.1	-0.1	-0.1	-0.1
2°C-CO		0.0	-0.2	-0.4	-0.2	-0.2		-2.2	-2.0	-1.3	-0.9	-0.8
NDC	phl	-0.1	0.0	0.1	0.4	0.8	xsa	0.1	0.2	0.9	0.8	0.9
NDC-CBAM		0.0	0.0	0.2	0.4	0.7		0.1	0.2	0.9	0.8	0.8
2°C		-0.3	-0.2	0.3	0.7	1.2		0.0	0.1	0.7	0.4	0.8
2°C-FTAX		0.1	0.5	0.3	0.8	1.0		0.1	0.3	1.2	0.6	0.6
<2°C		-0.4	-0.3	0.3	1.5	1.3		0.0	0.0	0.7	0.5	0.8
<2°C-EARLY		-0.4	-0.4	0.4	1.5	1.5		0.0	0.2	0.8	0.3	1.1
NDC-CO		-0.2	-0.3	0.0	0.2	0.2		-0.3	-0.6	-1.1	-1.0	-0.3
2°C-CO		-0.4	-0.4	0.1	0.6	1.1		-0.5	-1.3	-2.2	-2.8	-1.2
NDC	rus	0.0	0.0	-0.1	-0.2	0.0	all	5.1	14.5	19.5	16.1	11.4
NDC-CBAM		0.0	0.0	-0.1	-0.3	0.1		5.7	15.9	21.3	17.9	13.4
2°C		0.0	0.0	-0.1	-0.6	-0.6		6.0	26.0	34.7	28.3	21.0
2°C-FTAX		0.0	0.0	-0.1	-0.4	-0.6		10.9	29.7	33.2	24.7	18.5
<2°C		0.0	0.0	-0.1	-0.6	-0.7		5.0	27.1	38.8	32.2	23.4
<2°C-EARLY		0.0	0.0	-0.1	-0.5	-0.5		7.3	34.4	48.0	40.0	31.2
NDC-CO		0.0	0.0	-0.1	-0.2	0.0		-2.7	-5.2	-8.7	-5.2	-7.0
2°C-CO		0.0	0.0	-0.1	-0.6	-0.6		-5.7	-5.1	-5.5	-4.6	-8.9

Source: Author's simulation using the ENVISAGE-GIDD model. Note: bra = Brazil, chn = China, e27 = European Union (27), egy = Egypt, hay = other high income, idn = Indomesia, ind = India, mar = Morocco, phl = Philippines, rus = Russian Federation, ssa = Sub-saharan Africa, tur = Turkeyi, usa = United States, xea = rest of East Asia, xec = Rest of Europe and Central Asia, xhy = Rest of high-income, xlc = Rest of Latin America and the Caribbean, xmn = Rest of Middle East and North Africa, xsa = Rest of South Asia.

Table A 5. Change in poverty headcount with respect to baseline in 2050, by ENVISAGE region and poverty line

Scenario	Code	Poverty line, PPP(2011)$					Code	Poverty line, PPP(2011)$				
		$2.15	$3.65	$6.85	$10.00	$20.00		$2.15	$3.65	$6.85	$10.00	$20.00
NDC	bra	0.00	0.02	0.01	0.07	0.05	ssa	0.11	0.35	0.23	0.15	0.11
NDC-CBAM		0.00	0.03	0.02	0.10	0.04		0.17	0.49	0.36	0.24	0.13
2°C		0.01	0.01	0.04	0.08	0.09		0.11	0.56	0.45	0.36	0.23
<2°C		0.02	0.03	0.03	0.07	0.11		0.08	0.28	0.52	0.44	0.34
<2°C-EARLY		0.03	0.04	0.07	0.12	-0.10		0.16	0.53	0.61	0.50	0.36
NDC	chn	0.00	0.00	-0.07	-0.30	0.00	tur	0.00	-0.01	-0.06	-0.18	-0.25
NDC-CBAM		0.00	0.00	-0.03	0.02	-0.05		0.00	0.01	-0.05	-0.18	-0.08
2°C		0.00	-0.01	-0.02	0.02	0.31		0.00	0.04	0.04	-0.01	-0.34
<2°C		0.00	-0.02	-0.02	0.02	0.30		0.00	0.06	0.05	-0.04	-0.24
<2°C-EARLY		0.00	-0.02	0.02	0.06	0.44		0.00	0.08	0.09	-0.02	-0.20
NDC	e27	0.00	0.01	0.00	0.00	-0.03	usa	-0.01	0.00	-0.06	-0.02	-0.08
NDC-CBAM		0.00	0.01	0.03	0.04	0.03		-0.01	0.00	-0.05	-0.02	-0.03
2°C		0.00	0.01	0.02	0.01	-0.01		-0.03	-0.05	-0.13	-0.09	-0.23
<2°C		0.01	0.01	0.02	0.01	-0.02		-0.04	-0.07	-0.13	-0.17	-0.36
<2°C-EARLY		0.01	0.01	0.02	0.01	-0.02		-0.04	-0.07	-0.13	-0.17	-0.35
NDC	egy	0.00	0.08	-0.05	0.08	0.18	xea	-0.01	-0.05	-0.23	0.15	0.21
NDC-CBAM		-0.06	0.05	-0.27	-0.40	-0.15		0.00	-0.03	-0.19	0.14	0.25
2°C		0.00	0.14	-0.13	-0.06	0.41		-0.02	-0.30	-0.71	0.02	0.30
<2°C		0.03	0.14	-0.11	-0.44	0.21		-0.02	-0.29	-0.64	-0.02	0.34
<2°C-EARLY		-0.04	0.02	-0.17	-0.08	0.56		-0.02	-0.27	-0.72	0.06	0.58
NDC	hya	0.10	0.25	0.02	0.00	-0.01	xec	0.03	0.18	0.45	0.56	0.93
NDC-CBAM		0.11	-0.55	-0.31	-0.06	-0.02		0.03	0.18	0.41	0.53	1.01
2°C		0.19	-0.53	-0.28	-0.09	-0.01		0.08	0.35	0.97	1.38	2.17
<2°C		0.18	0.16	0.02	0.01	-0.02		0.10	0.38	1.10	1.65	2.41
<2°C-EARLY		0.26	-0.47	-0.32	-0.08	-0.04		0.11	0.42	1.17	1.73	2.59

Source: Author's simulation using the ENVISAGE-GIDD model. Note: bra = Brazil, chn = China, e27 = European Union (27), egy = Egypt, hay = other high income, idn = Indomesia, ind = India, mar = Morocco, phl = Philippines, rus = Russian Federation, ssa = Sub-saharan Africa, tur = Turkeyi, usa = United States, xea = rest of East Asia, xec = Rest of Europe and Central Asia, xhy = Rest of high-income, xlc = Rest of Latin America and the Caribbean, xmn = Rest of Middle East and North Africa, xsa = Rest of South Asia.

Table A 5. Change in poverty headcount with respect to baseline in 2050, by ENVISAGE region and poverty line (cont.)

Scenario	Code	Poverty line, PPP(2011)$					Code	Poverty line, PPP(2011)$				
		$2.15	$3.65	$6.85	$10.00	$20.00		$2.15	$3.65	$6.85	$10.00	$20.00
NDC	idn	-0.03	-0.08	0.05	0.19	0.13	xhy	0.00	0.00	0.00	0.01	-0.01
NDC-CBAM		-0.03	-0.05	0.03	0.18	0.21		0.00	0.00	0.00	0.01	0.06
2°C		-0.11	-0.11	0.22	0.45	0.43		0.00	0.01	0.01	0.00	-0.03
<2°C		-0.12	-0.14	0.15	0.39	0.64		0.00	0.01	0.01	-0.02	-0.07
<2°C-EARLY		-0.13	-0.15	0.39	0.69	0.86		0.01	0.01	0.01	-0.02	-0.05
NDC	ind	0.21	0.67	0.63	0.57	0.11	xlc	0.08	0.20	0.10	0.01	-0.01
NDC-CBAM		0.19	0.67	0.86	0.56	0.18		0.08	0.15	0.06	0.05	0.04
2°C		0.32	1.29	1.62	1.16	0.26		0.03	0.16	0.10	0.12	0.17
<2°C		0.39	1.43	1.84	1.21	0.31		0.06	0.16	0.15	0.20	0.30
<2°C-EARLY		0.41	1.67	2.10	1.38	0.51		-0.01	0.08	0.14	0.28	0.40
NDC	mar	0.09	0.21	0.38	-0.40	-0.16	xmn	0.05	0.05	0.03	0.03	0.08
NDC-CBAM		0.02	0.49	0.31	-0.10	-0.03		0.15	0.19	0.14	0.18	0.12
2°C		0.05	0.42	0.07	-0.17	-0.08		-1.00	-0.94	-0.56	-0.39	-0.34
<2°C		0.05	0.10	-0.10	-0.56	0.01		-1.19	-1.07	-0.59	-0.50	-0.38
<2°C-EARLY		0.02	0.35	0.14	-0.11	0.05		-1.05	-0.97	-0.51	-0.43	-0.35
NDC	phl	-0.06	0.01	0.15	0.37	0.46	xsa	-0.14	0.05	0.47	0.32	0.14
NDC-CBAM		-0.03	-0.01	0.18	0.36	0.38		-0.07	0.03	0.47	0.27	0.08
2°C		-0.18	-0.17	0.19	0.58	0.79		-0.22	-0.18	0.40	-0.37	-0.29
<2°C		-0.24	-0.17	0.23	0.67	0.88		-0.13	-0.16	0.16	-0.47	-0.25
<2°C-EARLY		-0.22	-0.24	0.45	0.74	0.92		-0.18	-0.02	0.12	-0.51	-0.27
NDC	rus	0.00	-0.01	-0.05	-0.20	-0.15	all	0.06	0.23	0.20	0.14	0.08
NDC-CBAM		0.00	-0.03	-0.03	-0.24	-0.12		0.08	0.26	0.28	0.20	0.09
2°C		0.00	-0.03	-0.07	-0.33	-0.88		0.05	0.35	0.44	0.32	0.18
<2°C		0.00	-0.04	-0.09	-0.51	-0.76		0.06	0.31	0.49	0.34	0.23
<2°C-EARLY		0.00	-0.04	-0.08	-0.75	-0.63		0.08	0.42	0.57	0.41	0.32

Source: Author's simulation using the ENVISAGE-GIDD model. Note: bra = Brazil, chn = China, e27 = European Union (27), egy = Egypt, hay = other high income, idn = Indomesia, ind = India, mar = Morocco, phl = Philippines, rus = Russian Federation, ssa = Sub-saharan Africa, tur = Turkeyi, usa = United States, xea = rest of East Asia, xec = Rest of Europe and Central Asia, xhy = Rest of high-income, xlc = Rest of Latin America and the Caribbean, xmn = Rest of Middle East and North Africa, xsa = Rest of South Asia.