Center for Global Trade Analysis
Purdue University

Distributional Impacts of Carbon Pricing Policies under Paris Agreement: Inter and Intra-Regional Perspectives

By

Maksym Chepeliev[1,2]

Israel Osorio-Rodarte[3]

and

Dominique van der Mensbrugghe[2]

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[1]Corresponding author email: mchepeli@purdue.edu. The authors acknowledge valuable comments on earlier draft by Sonja Peterson, Nick Macaluso and participants of the 23rd Annual Conference on Global Economic Analysis (Virtual Meeting).

[2] Center for Global Trade Analysis, Purdue University.

[3] The World Bank.

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Abstract

While bringing multiple benefits for the environment, achievement of the stringent global greenhouse gas emissions reduction target, like the one outlined in the Paris Climate Agreement, is associated with significant implementation costs and could impact different dimensions of human well-being, including welfare, poverty and distributional aspects. In this paper, we analyze the poverty and distributional impacts of different carbon pricing mechanisms consistent with reaching the Paris Agreement targets. We link a global recursive dynamic computable general equilibrium model ENVISAGE with the GIDD microsimulation model and explore three levels of mitigation effort and five carbon pricing options (trade coalitions). Results suggest that while there is a higher incidence of poverty in all scenarios, mainly driven by lower economic growth, Nationally Determined Contribution (NDC) policies result in progressive income distribution at the global level. Such progressivity is caused not only by lower relative prices of food versus non-food commodities, but also by a general decline in skill wage premia.

Achievement of the NDC targets without regional cooperation results in 0.45% increase in the number of people living in extreme poverty (below PPP$1.90/day) by 2030, while a more ambitious 2ºC-consistent target increases this number to 1.25%. Global cooperation significantly eases the burden on poor, reducing the poverty headcount (additional number of people leaving in extreme poverty) by almost three times in the case of 2ºC-consistent target and bringing it to the baseline scenario level in the case of NDC target. The global Gini coefficient falls between 0.01 and 0.04 percentage points depending on the mitigation effort and collaboration mode, while reduction in the Theil index is between 0.01 and 0.11 percentage points. Results also indicate that the reductions in inequality come mainly from reduction in income from top earners, as the results are much more sensitive to the NDC policies closer to the top of the income distribution.

Keywords: Paris Agreement; carbon pricing; distributional impacts; global assessment; microsimulation model; computable general equilibrium model.
JEL codes: C68; C83; D31; O15; Q54.

1. Introduction

With all-time high levels of greenhouse gas (GHG) emissions in 2018 (Le Quére et al., 2018) the debate over real actions to combat climate change has heated up. To meet the Paris Agreement target of a temperature increase below 2^{o}C would require a significant boost of the current policy efforts (Rogelj et al., 2016). Even to stay on track with the Nationally Determined Contributions (NDCs) communicated by countries would require a change of the current policy trajectory (UNFCCC, 2020).

Although bringing multiple benefits to the environment, achievement of the stringent global GHG emissions reduction target is associated with significant implementation costs and could impact different aspects of human well-being. Several studies have shown that carbon taxation could result in regressive distributional impacts for households (Ohlendorf et al., 2018) and that the properly designed compensatory measures should be implemented to avoid such regressive outcomes (Haug et al., 2018).

While climate change mitigation requires global action, distributional impacts of carbon policies are country specific, which defines the regional focus of most of the available studies (e.g. see overviews provided in Ohlendorf et al., 2018; Wang et al., 2016; Markkanen, S. and Anger-Kraavi, 2019). Existing studies with international coverage either focus on intercountry distribution (e.g. Padilla and Roca, 2004; van Vuuren et al., 2009; Wesseh and Lin, 2016) or provide insights into the potential distributional impacts (by household types) of the uniform carbon taxes in developing countries (e.g. Dorband et al., 2019).

Available literature suggests mixed implications on poverty and inequality. Dorband et al. (2019) find progressive income impacts for the low-income countries and mostly regressive for the middle-income economies. Meta-analysis by Ohlendorf et al. (2018) also suggests mostly progressive impacts in lower income countries. Some studies support the point of the regressive implications of the economy-wide CO_2 prices or increasing cost of energy in the high-income countries (e.g. Ekins et al., 2011; Frondel et al., 2015; Wier et al., 2005), while other report progressive impacts (e.g. Montenegro et al., 2019). Results for the developing countries are even more diverse. For instance, in the case of Indonesia Nurdianto and Resosudarmo (2016) report regressive impacts of carbon taxation, while Yusuf (2008) reports progressive implications. Impacts seem to largely depend on differences in methodological approach and recycling mechanisms (e.g. Vandyck and Van Regemorter, 2014), though in some cases impacts show the same distribution under varying recycling schemes (e.g. Yusuf, 2008).

While reporting many cases with country or region-specific climate policy incidence assessments, the available literature lacks an assessment of distributional impacts of the climate mitigation policies consistent with the active international commitments, such as the NDCs, and implemented at a multi-region scale.

To fill this gap, in this paper, we analyze the poverty and distributional impacts of different carbon pricing mechanisms consistent with reaching the NDC targets. For this analysis, we link a recursive dynamic computable general equilibrium (CGE) Environmental Impact and Sustainability Applied General Equilibrium (ENVISAGE) model (van der Mensbrugghe, 2019) with the Global Income Distribution Dynamics (GIDD) microsimulation model (Bussolo et al., 2010). We rely on the baseline scenario with energy and emissions profiles based on the World Energy Outlook (IEA, 2018) projections. We further consider three policy scenarios, which we impose on top of the baseline pathway – NDC (consistent with unconditional NDC targets), NDC+

(consistent with conditional NDC targets) and NDC-2C (scenario consistent with a 2°C pathway). To achieve the carbon emissions reduction target, we consider different carbon pricing options, including a no trade scenario, global trade in carbon (CO_2) and several options of partial sectoral and/or regional trade coalitions.

We first estimate the impacts of NDC pathways under different carbon pricing mechanisms using the ENVISAGE CGE model and then link these outcomes to the GIDD modelling framework to estimate the distributional consequences of the climate policies. In this way, we are able to capture both inter and intra-country distributional impacts of the NDCs. To our knowledge, this is the first study that provides an impact assessment of the NDC policies on poverty and income distribution in a multi-regional framework.

The rest of the paper is organized as follows. Section 2 provides an overview of the methodological framework. Section 3 overviews baseline and policy scenarios. Section 4 discusses macroeconomic, sectoral and distributional impacts of the carbon pricing policies. Finally, Section 5 concludes.

2. Methodological framework

In this section, we provide an overview of the methodological framework that we use in the following sections to provide an assessment of the carbon pricing policies under the Paris Agreement. We first describe the dynamic CGE model ENVISAGE (van der Mensbrugghe, 2019), we then proceed with an overview of the GIDD microsimulation modelling tool (Bussolo et al., 2010), followed by the discussion of the approach to linking these two models. The latter step is performed via a one-way model linkage, where selected outputs from ENVISAGE are transferred to the GIDD model to estimate the distributional impacts of the carbon pricing policies.

2.1. The ENVISAGE model

The ENVISAGE model (van der Mensbrugghe, 2019) at its core is a recursive dynamic and global CGE model. It follows the circular flow of an economy 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 determine 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 the aim of which is 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. In contracting sectors, *Old* capital is sold on secondary markets 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 (2019).

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.[4]

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, 2016a). The latter includes 11 electricity generation technologies, as well as an electricity transmission and distribution activity. For the purposes of this paper, we use an aggregation that includes 28 regions (Appendix B) and 29 sectors (Appendix C).

2.2. GIDD model

The GIDD model is used to estimate 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 survey to distribute macroeconomic shocks obtained from the CGE model. GIDD was developed by the World Bank (Bussolo, De Hoyos, and Medvedev 2010), inspired by previous efforts involving simulation exercises (Bourguignon, Ferreira, and Leite 2008; Bourguignon, Bussolo, and Pereira de Silva 2008; Davies 2009). As in most top-down modeling frameworks, the CGE drives most of behavioral responses. The microsimulation (down) distributes observed changes in a predefined set of linkage aggregate

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

variables that communicate the two models. During the transmission of shocks, a key element is to maintain consistency with observed changes from macro driven behavior.

The GIDD model relies on a collection of 130 nationally representative household surveys compiled by the World Bank with harmonized variables on demographics, education, labor, welfare and consumption.[5] It provides a cross section of surveys using 2011 as a base year. The sample covers more than 10.5 million individuals, constituting 83.4% of the global GDP and 86.3% of the global population (Table 1). The data is described with more detail in Ahmed, et al. (2020). With respect to the regional aggregation in this paper, the data in GIDD provides a consistent coverage for most of the aggregate regions and individual countries, with three exceptions. The GIDD does not contain household surveys for Korea, Japan, and Saudi Arabia.[6]

Table 1. GIDD database coverage

Region	GDP PPP$,B		Population, M		Microdata obs.
	Total	%	Total	%	
Low & middle-income countries	21,264.3	91.1	5,782.3	86.9	5,250,767
East Asia & Pacific	9,165.9	96.1	1,991.8	93.6	857,621
Europe & Central Asia	1,788.1	86.1	268.7	71.5	310,834
Latin America & Caribbean	5,291.8	98.6	585.6	98.0	1,472,436
Middle East & North Africa	1,275.6	21.3	343.9	19.4	70,402
South Asia	2,293.4	93.5	1,675.0	89.0	727,044
Sub-Saharan Africa	1,449.6	96.6	917.2	91.2	1,812,430
High-income countries	47,632.1	78.9	1,277.2	78.6	5,106,068
World	**68,896.4**	**82.7**	**7,059.4**	**85.4**	**10,356,835**

Source: developed by authors.

2.3. ENVISAGE and GIDD models' linkage

To provide an assessment of the distributional impacts of carbon taxes, we implement a soft linkage between the ENVISAGE and GIDD models. Figure 1 provides an overview of the general approach.

In the *first step*, we calibrate the baseline scenario for the ENVISAGE model (this step is discussed in more details in Section 3.1), including implementation of the macroeconomic and demographic assumptions. 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, as discussed in the Section 3.2, to estimate the set of 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

[5] The data include household surveys harmonized by the Poverty and Equity Global Practice of the World Bank and the International Income Distribution Database (I2D2). The 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 Maximilian (2009).

[6] Another important caveat inherent to household survey data is the lack of representation of individuals in both tails of the income distribution. On the left-side, the homeless poor are not part of the sampling framework. On the right side, incomes of top earners above the 1% of the distribution are not fully captured with typical instruments in survey questionnaires.

consumer price index (CPI) are estimated for the food and non-food component; wages are estimated for skilled and unskilled workers in agricultural and non-agricultural sectors. These estimates are done in the separate post-simulation routine, which we call "Income/expenditure change estimator" (Figure 1). In the *third step*, processed ENVISAGE outputs are passed to the GIDD model. Prior to this, GIDD model is calibrated to match the baseline assumptions of the ENVISAGE run, in particular, macroeconomic and demographic profiles. Finally, in the *fourth step*, GIDD model implements shocks in the selected variables to estimate the distributional impacts of the carbon pricing. We discuss *Step four* in more detail below.

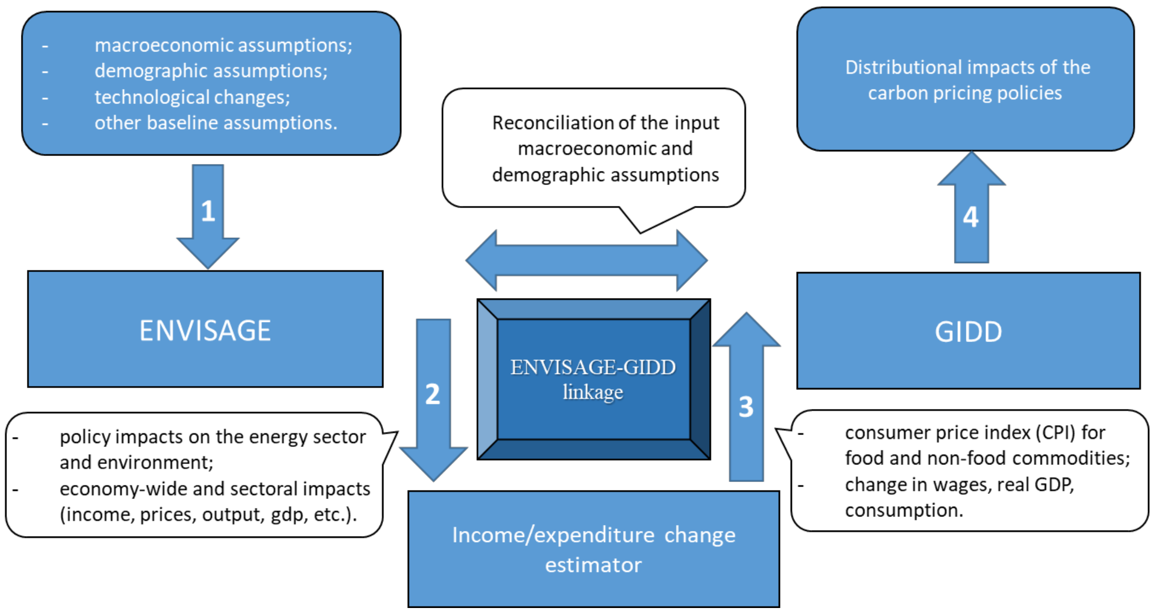

Figure 1. Overview of the general approach to the ENVISAGE-GIDD linkage
Source: developed by authors.

ENVISAGE (macro) and GIDD (micro) models are connected through changes in labor supply, skill formation, and real earnings. 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, 2017). The GIDD framework, in addition, reallocates workers across sectors based on aggregate general equilibrium conditions. After reallocation, the GIDD simulates impacts on real earnings, income growth, and changes in relative prices for food and non-food expenditures. The shocks are transmitted through a set of linkage aggregate variables that connect macro and micro models.

The first step in the microsimulation exercise is to implement a set of changes in the household surveys' demographic structure. The population growth adjustment is particularly important in countries with rapid demographic changes. The adjustment for population growth allows the analysis to explicitly take into account 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 in creating the baseline scenario for the ENVISAGE model. 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 educational 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 earning of 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 from shrinking into expanding sectors. The sectoral reallocation process estimates the probability of each worker to be reallocated into new sectors, based on individual characteristics. Once workers are reallocated, a new vector of earning 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 sectors 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 micro data and feed into the global CGE model. It is important 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 exactly 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. When information about the relationship between income and savings exists, in both micro and macro models, this can be incorporated. In most circumstances, it is absent in household survey data, as is the case for this paper. In this case, a one-to-one passthrough from per capita household income to consumption is assumed. In this regard, 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 and non-food shares can be adjusted estimating a Lorenz's curve of budget share expenditure on food vis-à-vis total per capita household consumption. These steps are explained in detail in Maliszewska, Osorio-Rodarte, and Gupta (2020).

Several studies have reported that the carbon revenue recycling scheme could have a major 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 option of the carbon revenue recycling, which is a lump-sum payment to the representative household within the ENVISAGE modelling framework. This approach to the 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 to 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 current study.

3. Carbon pricing scenarios

In this section, we first provide an overview of the calibration of the baseline scenario. The baseline assumptions are used to match the energy and emission pathways from the World Energy Outlook (WEO) projections.[7] Three policy scenarios, with different levels of mitigation effort, are considered and imposed on top of the baseline pathway. To achieve the carbon emissions reduction target, we consider different carbon pricing options, including a no trade scenario, global CO_2 trade and several options of partial sectoral and/or regional trade coalitions.

3.1. Baseline calibration

The WEO baseline scenario is calibrated to match CO_2 emissions[8] and GDP growth rates at the regional (country) level for the 2011-2030 timeframe. In the calibration process, labor productivity is adjusted to match the GDP growth rate targets for each region. Additional baseline assumptions include declining changes in the cost of renewable electricity generation, non-price related changes in preferences towards renewables, increases in electricity shares for the final and intermediate consumers, improvements in energy efficiency, reduction in international transportation costs and targeting of crude oil price trends. No carbon prices are introduced within the baseline pathway. Appendixes D, E and F provide additional details on the baseline calibration assumptions.

Though the developed baseline emission pathways do not exactly match CO_2 profiles of the WEO baseline, in most cases, the difference between developed and targeted emissions in 2030 is less than 4% (Figure 2).[9] The only exception is France, where the ENVISAGE-based baseline emissions are higher than those reported in the WEO (Figure 2).

In the case of France, WEO reports that baseline emissions in 2030 would fall by 22% relative to the 2011 level. In 2011, the share of total primary energy supply (TPES) from non-fossil fuels was already around 52% (IEA, 2020) and further aggressive reduction of CO_2 emissions would require implementation of the stringent mitigation measures, not included in the ENVISAGE baseline calibration approach.

[7] These have been provided by the EMF-36 principal investigators and are based on the 2018 WEO (IEA, 2018) prospects.

[8] We consider CO_2 emissions from fossil fuel combustion only.

[9] We also compared the emission profiles by sector at the global level. WEO reports global CO_2 emissions for the transportation and power sectors. Over 2016-2030 WEO reports 1.5% annual growth rate in global CO_2 emissions in transportation (Current Policies scenario), while in our baseline corresponding emissions grow by 1.3% per year. In the case of power generation, WEO reports 1.0% annual growth rate in global CO_2 emissions, while our baseline results in the 0.6% annual average growth rate.

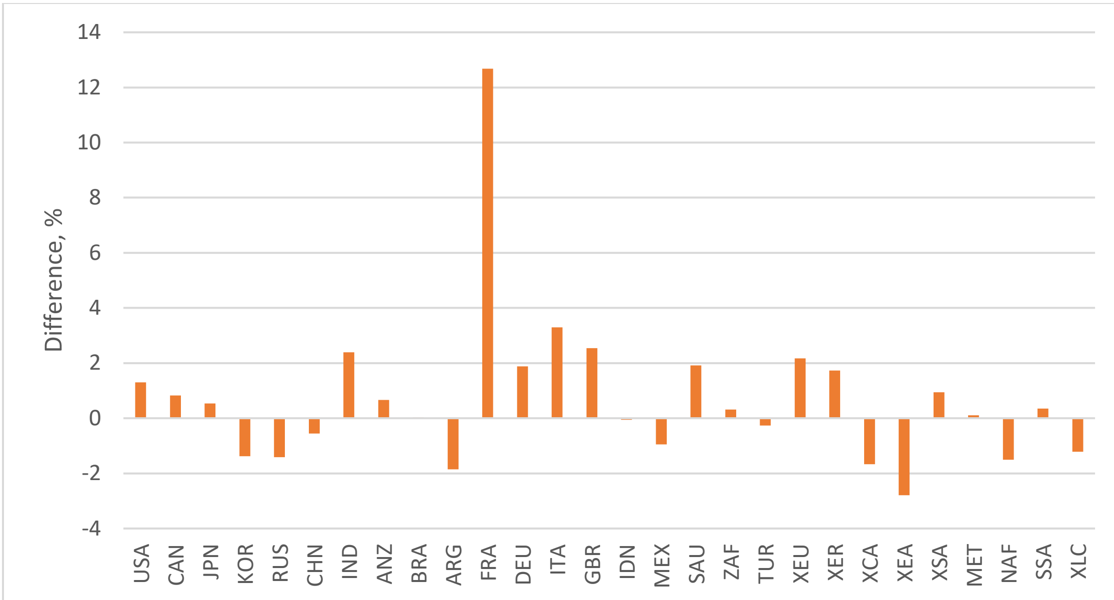

Figure 2. Difference between 2030 CO_2 emissions under calibrated pathways and baseline emissions reported in the WEO, %

Source: developed by authors based on IEA (2018) and ENVISAGE model simulations.

Notes: a positive deviation means that ENVISAGE-based emissions are higher than under the WEO baseline.

3.2. Policy scenarios

Carbon mitigation targets relative to the baseline emission pathway are defined based on three alternative mitigation efforts. Table 2 provides an overview of these alternatives. Conditional and unconditional NDC targets at the country level are adapted from Vandyck et al. (2016). These targets are further aggregated using baseline emissions as weights to match the regional aggregation (Appendix B). "NDC-2C" scenario targets are obtained by scaling the "NDC+" scenario targets, so that emission reductions are consistent with the 2°C pathway (Böhringer et al., 2020). For the policy simulations, 2030 emission reduction targets are implemented linearly starting from 2020.

Table 2. Emissions reduction scenarios

No.	Mitigation scenario	Description
1.	NDC	Includes a translation of unconditional NDCs into regional emission reduction requirements for 2030 relative to the baseline in 2030.
2.	NDC+	Includes a translation of conditional NDCs into regional emission reduction requirements for 2030 relative to the baseline in 2030.
3.	NDC-2C	Includes regional emission reduction targets for 2030 based on NDCs such that global emissions are on a 2°C path.

Source: Böhringer et al. (2020).

Notes: NDC targets are estimated at the country level. Weighted average aggregation is then used to map the emission reduction requirements (at the country level) to the aggregate regions.

For each emissions reduction scenario, five cooperation options are considered (Table 3). The first cooperation scenario ("REF") represents the most expensive way (global average) of reaching the NDC targets, as no regional cooperation is assumed and countries/regions reach reduction targets individually.[10] The second scenario ("GLOBAL") corresponds to the cheapest way (global average) of reaching the NDC targets, as global emissions trading for all sectors is assumed. The third scenario ("PARTIAL") corresponds to the global emissions trading system (ETS), but between energy intensive and trade exposed (EITE) sectors only, while other sectors do not trade. EITE sectors are identified in Appendix B. Two remaining cooperation scenarios ("EU-CHN" and "ASIA") represent different ETS regional coalitions. Under both of these scenarios, it is assumed that emissions trading is taking place across all emitting agents.

Table 3. Cooperation scenarios

No.	Cooperation scenario	Description
1.	REF	Regions achieve emission reduction requirements through regional action, i.e. regionally uniform CO_2 prices
2.	GLOBAL	Global trading across all sectors, i.e. globally uniform CO_2 price
3.	PARTIAL	Global trading only in EITE sectors
4.	EU-CHN	Club-trading: EU and China link ETS for EITE sectors
5.	ASIA	Club-trading: China, Japan, and Korea link ETS for EITE sectors

Source: Böhringer et al. (2020).
Notes: list of the energy intensive and trade exposed (EITE) sectors is provided in Appendix C.

4. Results

In this section, we focus on the key economic implications of carbon pricing under Paris Agreement. We first briefly present macroeconomic and sectoral impacts at the aggregate (regional/country) level. We then move to the assessment of distributional impacts on households. We focus on two cooperation scenarios—"REF" and "GLOBAL", as the two pathways representing higher and lowest emissions reduction costs among all five cooperation scenarios (Table 3). As would be discussed in Section 4.1, other collaboration modes ("PARTIAL", "EU-CHN" and "ASIA") do not bring any significant reduction to the climate mitigation costs. All results presented in this section are reported as changes relative to the corresponding baseline values in 2030.

One important point that should be highlighted in terms of the overall modelling approach and results interpretation is that in this paper we consider CO_2 emissions from fossil fuel combustion only. Thus, we neither take into account CO_2 emissions from other sources (e.g. industrial CO_2 emissions or CO_2 emissions from land use activities) nor do we consider non-CO_2 GHGs, which are largely associated with agricultural activities (e.g. enteric fermentation, manure management, rice cultivation, etc). Inclusion of these emission categories to the climate mitigation policies assessment might change aggregate results and distributional impacts, as mitigation efforts would change by sectors. Studies have shown that such alternative policies can come at a lower overall economic cost than taxing fossil fuels only, though may be more difficult to implement (e.g. van Vuuren et al., 2006). Other studies explore difference in regional impacts for CO_2 vs mutli-gas mitigation efforts, suggesting lower burden of emission reduction policies on the large

[10] While EMF-36 protocols require submission of the results for 14 regions (Appendix B), we use an aggregation with 28 regions (Appendix B). In the "REF" case, we assume that emission trading takes place between countries/regions that are mapped to the single region in the EMF-36 protocols. For instance, single region Europe (EUR) in the EMF-36 protocols corresponds to six countries/regions in our aggregation—France, Germany, Italy, United Kingdom, Rest of Europe, Rest of EU and EFTA. Therefore, we assume a uniform carbon price within these six countries/regions under "REF" scenario.

energy exporters and consequently more negative impacts for net energy importers in the latter case (e.g. Ghosh et al., 2012). Although it should be noted that within the Paris Agreement contributions different countries committed to the reduction of different GHGs. This ranges from CO_2 emissions reduction from fossil fuels combustion only in the limited set of sectors to commitments to act on both CO_2 and non-CO_2 greenhouse gas emissions (UNFCCC, 2020).

4.1. Inter-regional implications

At the global level, carbon pricing policies result in moderate reductions in welfare,[11] as it falls by around 0.35% under the "NDC" mitigation scenario and "REF" collaboration case. A reduction of 1.16% in global welfare is observed for the case of "NDC-2C" mitigation efforts and "REF" collaboration (Figure 3). Implementation of the "ASIA" ETS does not have any substantial impact on the global welfare, as even under "NDC-2C" mitigation effort it brings around 0.02% increase in welfare relative to the "REF" case. "PARTIAL" and "EU-CHN" cooperation scenarios increases global welfare by around 0.06% under the "NDC" scenario and 0.1% under the "NDC-2C" (relative to the "REF" case). While change in global welfare is almost the same under "EU-CHN" and "PARTIAL" collaboration modes, the latter one results in substantially lower weighted standard deviation in welfare by regions, thus providing a more equal distribution of welfare losses (Figure 3). Transition to "GLOBAL" cooperation case not only significantly lowers global average welfare losses, but also makes their distribution by counties more uniform (Figure 3), thus supporting improvements in social equity.

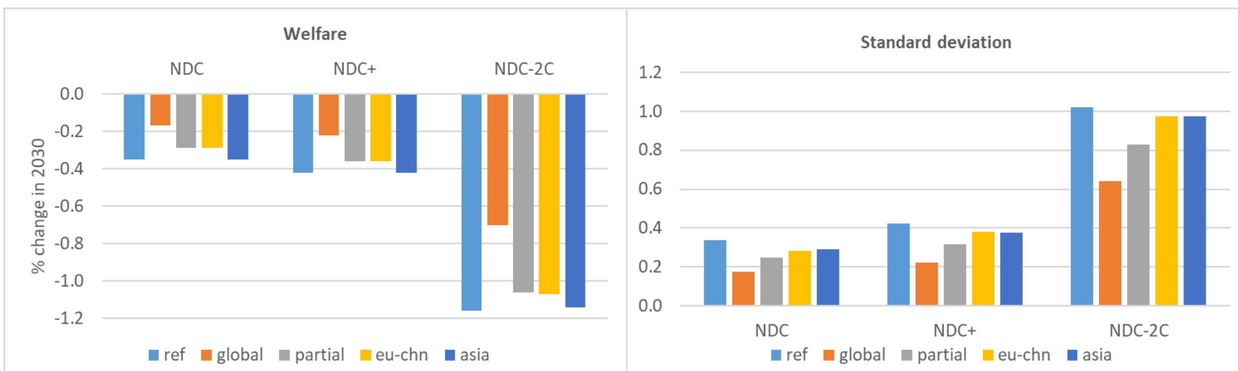

Figure 3. Global welfare impacts and standard deviations from the global average

Source: estimated by authors.

Notes: weighted standard deviation is reported; 2030 baseline welfare values (in constant $2011) are used as weights.

There is a moderate trend towards regressive distribution of the welfare impacts by regions, as countries with lower per capita real income tend to face somewhat higher reductions in welfare (Figure 4). There are two key factors behind this outcome. First, emission reduction targets are only moderately progressive relative to the per capita welfare level (Figures G.1, G.2, Appendix G), meaning that in terms of relative emission reductions developing countries are committing to almost the same level of effort as advanced economies (and although the cost of emission reductions is much lower in the case of developing countries, carbon intensities of their economies are on average higher). Resulting carbon prices are highly heterogenous by regions, with price above \$100/tCO_2-eq.[12] (for the "NDC" targets and "REF" cooperation) being observed for both

[11] Changes in economic welfare are estimated using the Equivalent Variation (EV) measure.

[12] Carbon price is reported per metric ton (1 metric ton = 1000 kg).

developing (e.g. Brazil, Other Asia) and high-income (e.g. Canada, South Korea, Europe) economies (Figures G.3-G.5, Appendix G). Second, a number of large fossil fuel exporters, such as Russia, Saudi Arabia, Indonesia, Rest of Central Asia, Middle Eastern and North African countries, face negative impacts of decreasing global demand for fossil fuels, even if their NDC commitment is not very ambitious. Per capital welfare in these economies is in most cases below global average and this drives the regressive distribution of welfare impacts by regions. Third, a number of developing net energy importers with relatively low-ambition mitigation targets experience small reductions in welfare, as they benefit from the decrease in global energy prices. These include China, India, Rest of Europe and Rest of South Asia (Figure 4).

One non-intuitive result at the regional level is a positive impact on welfare in Korea for almost all collaboration modes and mitigation efforts (GDP though falls substantially). This should be also considered in the context of ambitious mitigation efforts accompanied by one the highest carbon prices, as only Brazil and Europe face higher CO_2 tax. To further explore such outcome, we have replicated emission reduction targets by regions using static GTAP-E model with a build-in welfare decomposition facility (McDougall and Golub, 2009). GTAP-E model simulations also suggest that Korea faces significant GDP reductions resulting from a high carbon price that needs to be imposed to meet the ambitious emission reduction target, but aggregate welfare improves. Welfare decomposition suggests that such improvements are largely driven by the positive terms of trade effects that outweigh the negative impacts on welfare from changes in allocative efficiency.

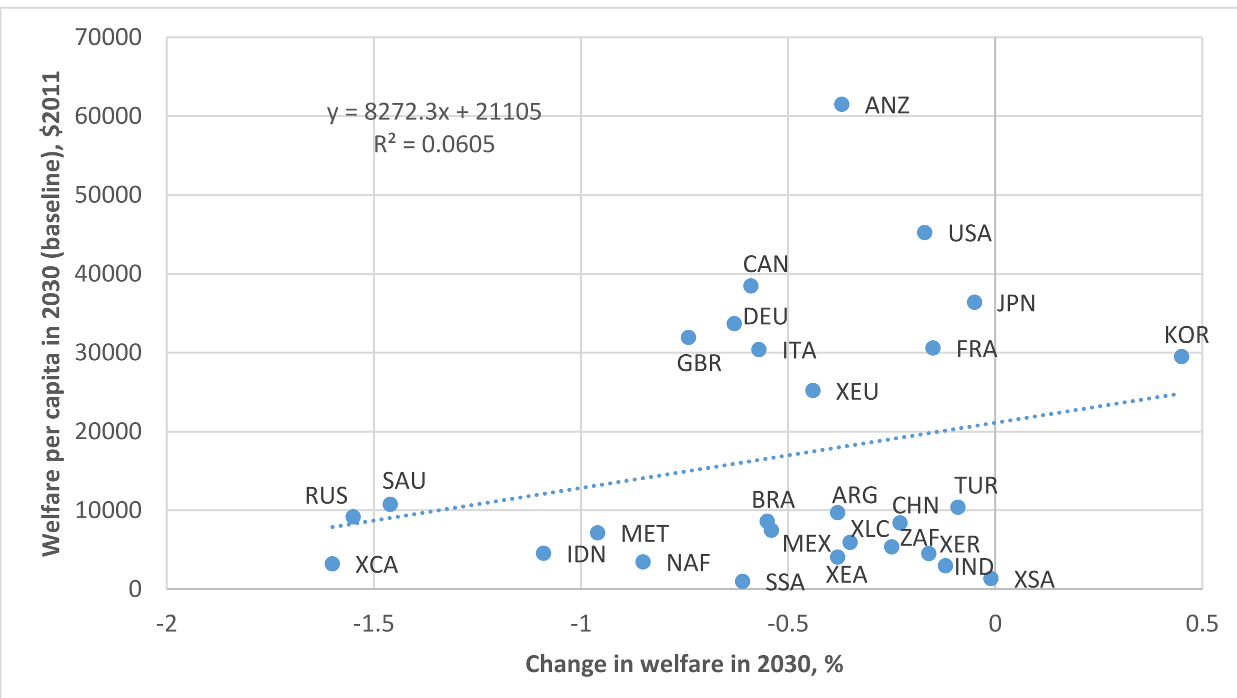

Figure 4. Change in welfare under "NDC" scenario and "REF" cooperation case vs per capita welfare in the baseline scenario in 2030

Source: estimated by authors.

Notes: each point represents one of the 28 regions (see Appendix B for the list of regions).

Although globally uniform carbon prices are associated with a more stringent mitigation efforts in the selected developing regions (compared to the "REF" cooperation case), in particular, South Africa, China and India, where emission reductions are cheaper than in the high-income economies, on average, distribution of the welfare impacts becomes more progressive (Figure 5). One of the drivers behind this trend is significantly lower welfare losses faced by major energy exporting countries, including Russia, Indonesia, Rest of Central Asia and Middle East (Figure 5). With much lower reduction in international energy prices, global exports of fossil fuels, so important for the economy of these countries, do not shrink so significantly, as under the case of "REF" cooperation. Global emission trading is particularly beneficial for the high-income countries with expensive emission reductions, such as EU countries and Canada, as with carbon permits trade they are able to achieve four to five times smaller welfare losses compared to the "REF" cooperation case (Figures 3, 4). Nevertheless, observed welfare outcomes under the "GLOBAL" cooperation case still support the need of financial transfers from richer to poorer countries to make the climate mitigation cost distribution more uniform under the case of global cooperation (e.g. Landis and Bernauer, 2012).

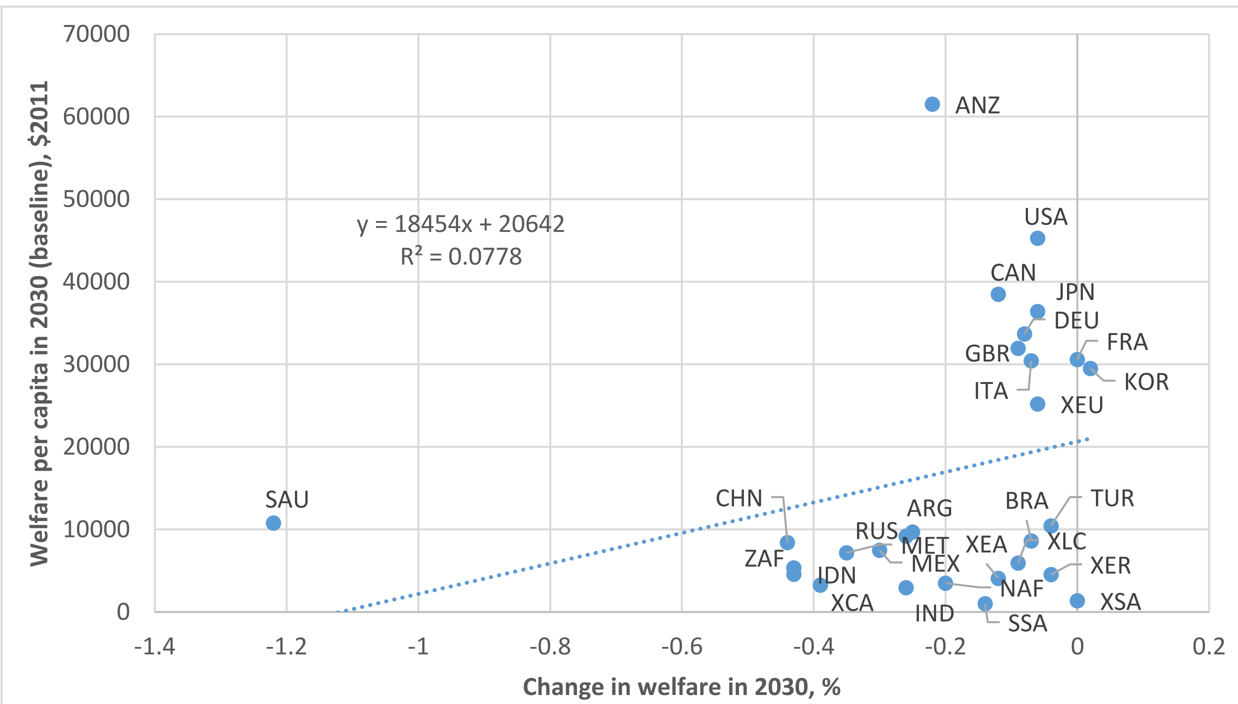

Figure 5. Change in welfare under "NDC" scenario and "GLOBAL" cooperation case vs per capita welfare in the baseline scenario in 2030

Source: estimated by authors.

Notes: each point represents one of the 28 regions (see Appendix B for the list of regions).

4.2. Poverty and distributional impacts on households

An increase in CO_2 tax puts pressure on energy prices, which in turn impacts the cost of food commodities, as fuel and transportation services increase in cost. On average, non-food commodities experience higher increase in prices than food commodities, as the first group includes energy and energy intensive goods (Figure 6). In a number of regions, food prices moderately decrease due to the lower global food demand (relative to the baseline path). Under "NDC" scenario non-food CPI reaches 5% in the case of Rest of Europe and around 2% in Korea and a number of European countries (Figure 6). Achievement of the 2^{o}C-consistent mitigation target ("NDC-2C" scenario) roughly doubles these numbers (Figure 6). Under the "GLOBAL" cooperation case, impacts on CPI are much lower than under the no-cooperation case, as in most countries non-food CPI increases by less than 1% under the NDC scenario (Appendix H). In some countries though, globally uniform carbon prices result in higher price increases (compared to the "REF" scenario). In particular, this is the case for Saudi Arabia, which has an unambitious unconditional NDC target and therefore faces a higher carbon price under global mitigation effort compared to the regional action scenario.[13]

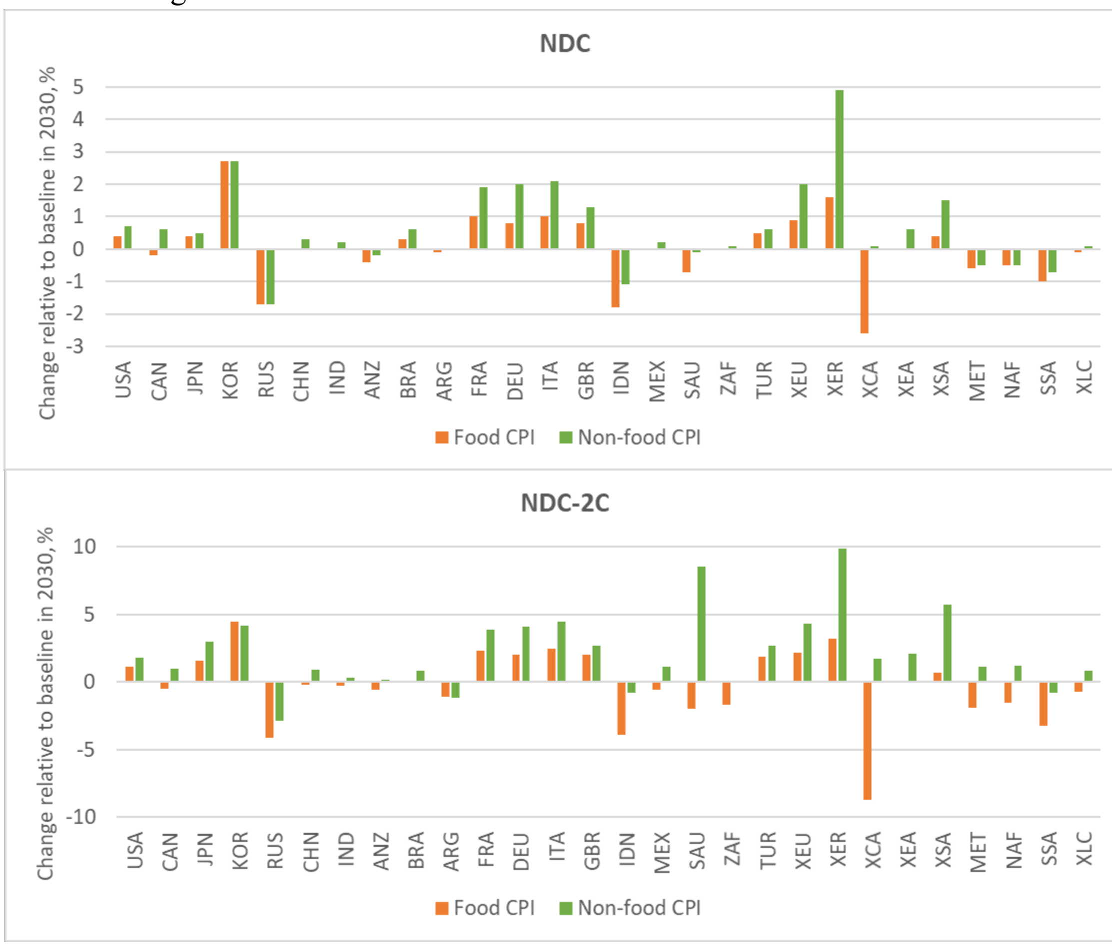

Figure 6. Changes in food and non-food consumer prices under the "REF" cooperation
Source: estimated by authors.

These trends in price changes (higher increase in non-food vs food CPI) combined with changes in aggregate growth rates by countries (lower GDP and welfare growth relative to the baseline scenario) shape two key outcomes of the distributional impacts assessment. The first of

[13] It should be noted that although Saudi Arabia faces higher carbon prices after entering global emissions trading scheme (compared to the "REF" cooperation case), welfare implications for the country are positive. While under "REF" cooperation case country's welfare falls by around 1.5%, under the "GLOBAL" cooperation welfare reduces by around 1.2% relative to the baseline scenario.

such trends is a higher incidence of poverty in all scenarios that result primarily from lower economic growth, which negatively impacts income of all households and thus increases the poverty level. The second trend is a progressive effect influenced by lower relative prices of food versus non-food commodities (as shown in Figure 6 above) and due to a general decline in skill wage premia (Figure 7).

For all analyzed regions, the share of households' income spent on food and beverages decreases with income. In some developing countries and regions lower quintiles spend up to 40%-60% of their income on food. For instance, this is the case for Argentina, Indonesia, India, Northern Africa, Mexico, Russia, Sub Saharan Africa, some Middle Eastern countries, Turkey, Rest of Central Asia, Rest of East Asia, Rest of Europe, Rest of South Asia (Appendix I). Relative reduction in food prices in these regions thus benefits lower income groups and results in progressive outcomes. Together, these regions account for over 60% of the global population, thus driving the global income distribution results.

This expenditure side effect is further supported by the income side trends. While in most countries wages fall for both skilled and unskilled workers, reduction in the skilled wages is higher than in the unskilled wages, particularly, in the developing countries. Due to the fact that in developing countries (e.g. China, India, Indonesia) mining and energy intensive sectors have higher share of skilled labor compared to agriculture, combined with the higher impact of carbon prices on energy intensive sectors, a decline in skill wage premia is observed. This is not the case for advanced economies (e.g. EU countries, USA, Canada), where the share of skilled labor in agriculture is higher than in the energy intensive sectors, although the share of labor employed in agriculture is also much lower than in the developing countries.

Apart from changes in relative wages, another important channel through which changes in the labor conditions affect income inequality, in the long run, is the movement of workers across different categories delineated by the four segments in the GIDD model: agriculture, non-agriculture, skilled workers, and unskilled workers. The four segments start from different initial point across regions of the world.

In most analyzed regions, there is an increase in agricultural employment (both for skilled and unskilled workers) and corresponding reduction in the employment in the non-agricultural sectors (Figure 7). This trend is driven by the fact that due to the higher carbon intensity of the non-food sectors and corresponding higher increase in the non-food prices, part of the labor force employed in these sectors is reallocated to agricultural industries. Under the higher level of mitigation effort (i.e. consistent with 2^{o}C), movement of labor force toward agricultural sector is more prevalent. However, it should be noted that in relative terms the effect of change in relative wages proves to be a more prominent factor in determining distributional impacts, compared to the channel of labor movement across different categories (Figure 7).

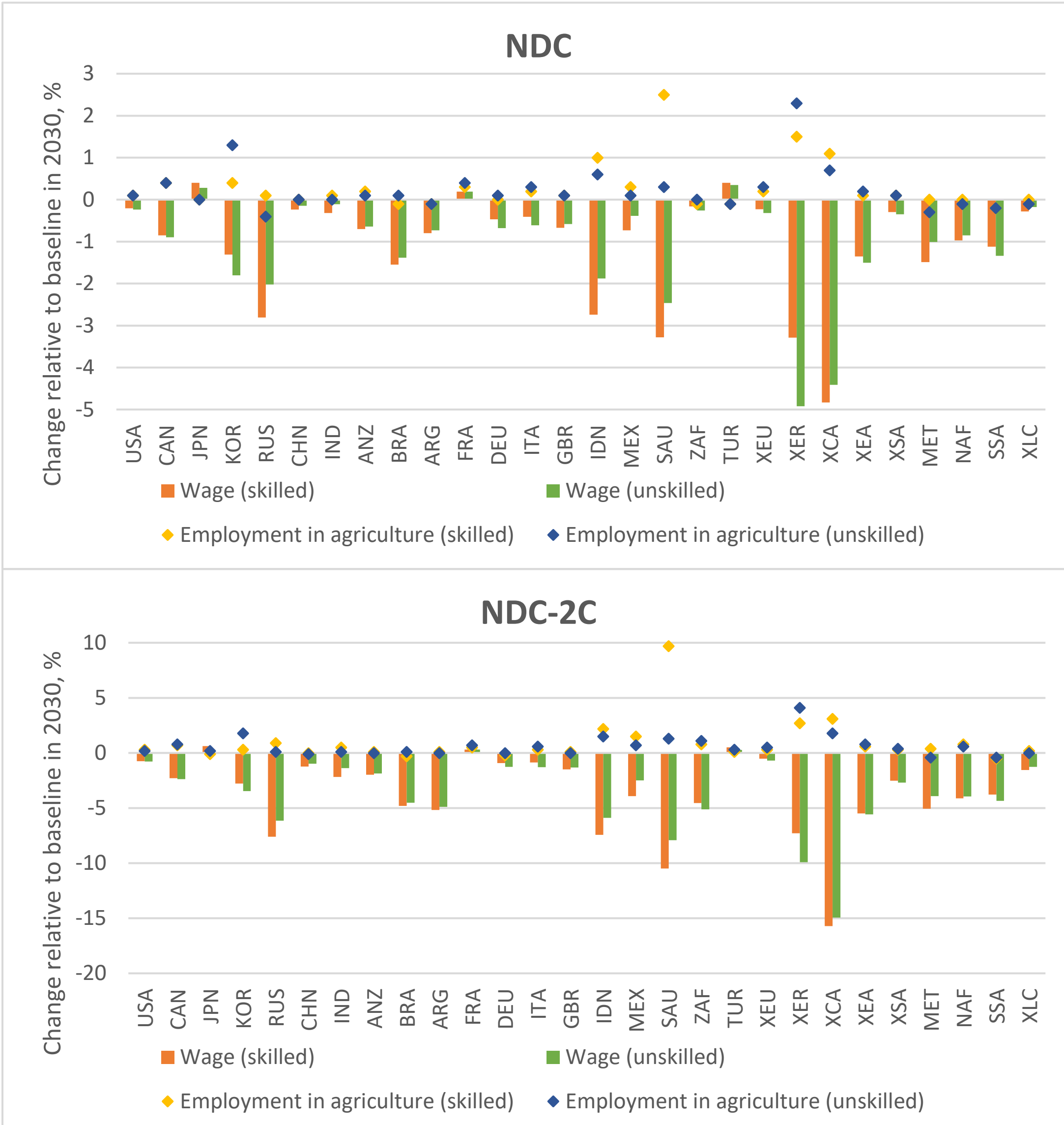

Figure 7. Changes in wages and employment in agriculture under the "REF" cooperation

Source: estimated by authors.

Notes: As we assume full employment in the ENVISAGE model, any increase (decrease) in the employment in agricultural sector is associated with corresponding decrease (increase) in the employment in the non-agricultural sector.

In terms of poverty, pursuing "Global" cooperation causes fewer negative impacts on poverty than "REF"; while mitigation schemes that are more ambitious and hence more stringent on economic growth are expected to create a larger incidence of poverty, all else equal. The level of extreme poverty in the baseline scenario is expected to decline following historical trends. Global extreme poverty, measured by the headcount ratio (%) of individuals living with less than PPP$1.90 a day, would go from 9.45% in 2020 to 8.81% in 2030 (Table 4).[14] Under "REF" cooperation and for the NDC, NDC+, and NDC-2C the global poverty headcount ratio (at PPP$1.90 a day) would reach 8.84%, 8.86%, and 8.92%, respectively. Similarly, under "Global"

[14] A discussion of the selected poverty indices used in this paper is provided in Appendix I.

cooperation and for NDC, NDC+, and NDC-2C scenarios, the global poverty headcount ratio would be 8.81%, 8.82%, and 8.85%. Accounting for the expected population growth, this implies that under "REF" cooperation there would be between 2.9 and 7.9 million additional people living in extreme poverty (PPP$1.90/day). In the case of a "Global" cooperation with the more ambitious "2C" target, it will push into poverty an additional 2.9 million, with respect to baseline by 2030 (Table 4).

The poverty line of PPP$1.90 a day is useful for measuring global extreme poverty with respect to a minimum floor. It has been rightly emphasized, however, that an absolute level at PPP$1.90 is not adequate for measuring poverty in countries with higher levels of income. It is practical to use additional international higher-value poverty lines that account for level of development in middle and high-income countries. Following the methodology of the World Bank (2018), Table 4 and Table 5 present summary statistics for global poverty with three higher-value poverty lines at PPP$3.20, PPP$5.50 and a notional line of PPP$10.00 per day that corresponds to global middle class.[15] Accounting for the expected population in 2030 of 7.18 billion, pursuing the 2C target would prevent for reaching middle-class status (above PPP$10.00 a day) between 18.7 and 23.7 million by 2030, for the "Global" and "REF" scenarios respectively.

Table 4. Poverty headcount ratios (%), poverty levels (millions) and difference to baseline, by scenario in 2030

Poverty line PPP$(2011)/day	Baseline	REF			Global		
		NDC	NDC+	NDC-2C	NDC	NDC+	NDC-2C
	%	Percentage point difference w.r.t baseline					
$1.90	8.81	0.04	0.05	0.11	0.00	0.01	0.04
$3.20	16.62	0.04	0.03	0.08	-0.01	0.01	0.01
$5.50	29.11	0.06	0.08	0.18	0.01	0.02	0.14
$10.00	49.25	0.10	0.09	0.33	0.08	0.08	0.26
	millions	Difference w.r.t baseline, millions					
$1.90	632.7	2.9	3.6	7.9	0.0	0.7	2.9
$3.20	1193.6	2.9	2.2	5.7	-0.7	0.7	0.7
$5.50	2090.6	4.3	5.7	12.9	0.7	1.4	10.1
$10.00	3537.0	7.2	6.5	23.7	5.7	5.7	18.7

Source: estimated by authors.

The negative effect of declining wage premia affects income growth for skilled workers, located at higher deciles of the income distribution. To illustrate this effect, Figures 8 and 9 show growth incidence curves (GICs) for "REF" and "Global" cooperation arrangements. GICs represent the gains or losses relative to the baseline across the income distribution. The horizontal axis of GICs indicates percentiles of the income distribution (in each country/region in the ENVISAGE model). On the vertical axis, GICs show per capita income growth with respect to the baseline, by 2030. Regressive effects are characterized by a positive slope in the GICs, while progressive effects exhibit a negative slope. In line with lower economic growth and higher incidence of poverty, most of the GICs in Figures 8 and 9 lie below the zero-horizontal line.

[15] The growth elasticity of poverty is higher at the center of the global distribution of income than at its tails, if the line is set closer to the middle of the global distribution of income, around PPP$10.00 a day, the effect of an additional unit of growth on poverty reduction is higher.

Consistent with previous findings, GICs for "Global" cooperation are above GICs for pursuing "REF" cooperation. Figures 8 and 9 present evidence of consistent progressive effects across scenarios, similar in direction to the effects in Dorban et al. (2019) for food prices. More importantly, the distributional results show that the slope of the GICs tend to exhibit more progressive results with the more ambitious "2C" target. Almost all regions show progressive income distribution under both "REF" and "GLOBAL" cooperation arrangements, though France and Turkey are the only exceptions in both cases, showing some regressivity of carbon pricing impacts. In the case of France and Turkey, the key driver of such impacts is an increase in wages, combined with an increase in the wage premia (Figure 7). It should be noted that this trend in wage changes is also observed for Japan, but the GIDD model does not contain household surveys for Japan and thus we do not estimate distributional impacts for this country.

Table 5 summarizes the insights of the GICs for the global sample with five inequality measures (definition of the poverty measures is provided in Appendix J). Inequality indices differ in their sensitivities to income differences in different parts of the distribution. The more positive '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 percentiles ratios of the individual in the bottom percentile 90 and in the top 10. Table 4 shows initial levels of each of these indicators, and negative differences with respect to WEO baseline by 2030. Moreover, GE(2) differences are higher in levels and in percentage terms, indicating that reductions in inequality come from reduction in income from top earners.

Table 5. Global inequality measures and difference to the baseline, by scenario

Poverty line PPP$(2011)/day	Baseline	Percentage point difference w.r.t baseline, by 2030					
		REF			Global		
		NDC	NDC+	NDC-2C	NDC	NDC+	NDC-2C
GE(0), %	83.09	-0.03	-0.03	-0.16	-0.06	-0.07	-0.14
GE(1), %	83.31	-0.03	-0.01	-0.11	-0.03	-0.03	-0.03
GE(2), %	257.57	1.10	-0.67	-1.18	-0.61	-0.87	-0.88
Gini coefficient, %	63.71	-0.01	-0.01	-0.04	-0.01	-0.01	-0.02
P90/P10	26.02	0.00	-0.04	-0.04	-0.06	-0.10	-0.16

Source: estimated by authors.

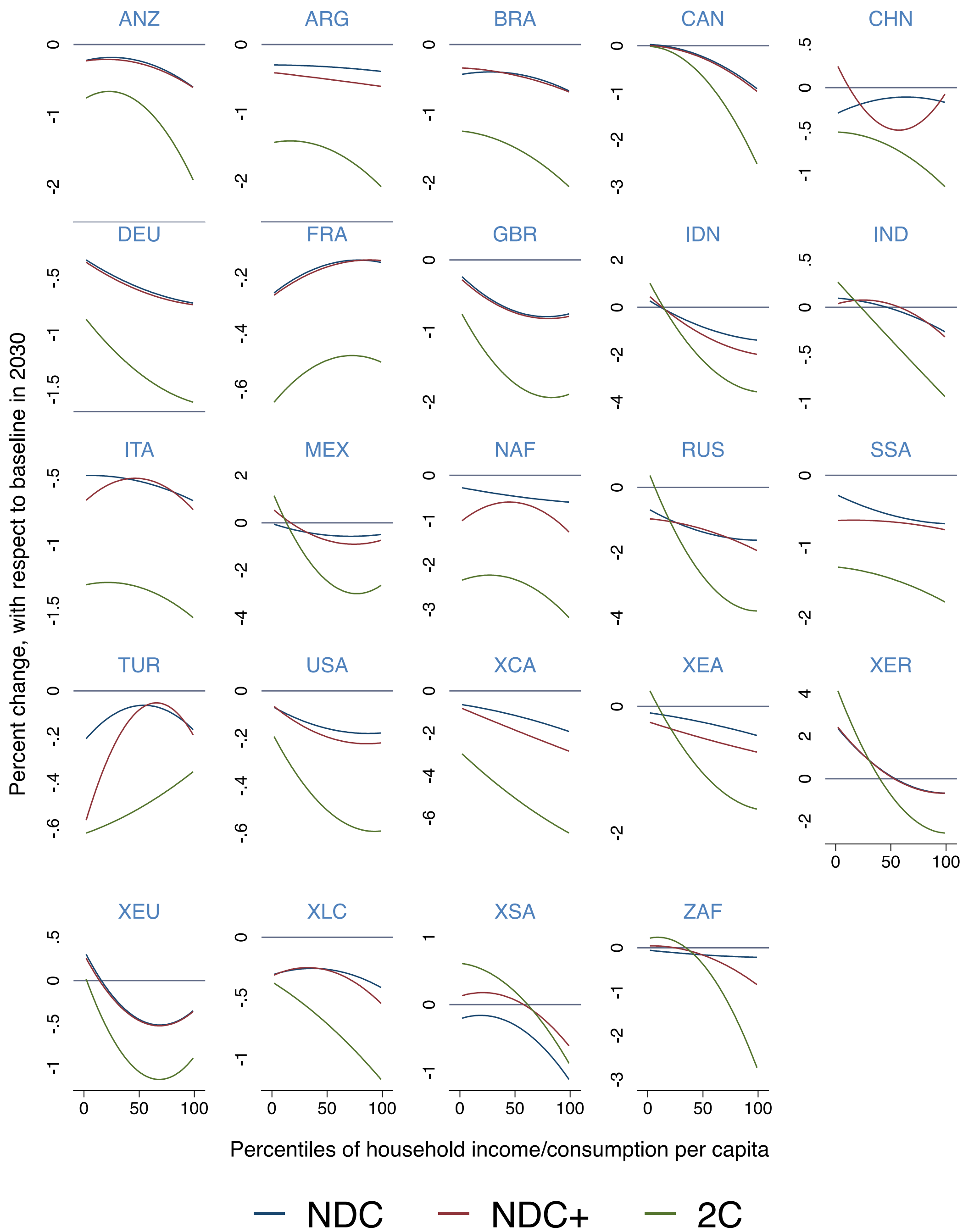

Figure 8. Growth Incidence Curves under the "REF" cooperation

Source: estimated by authors.

Notes: Results for the "MET" region are not reported, due to the unreliable survey data and incomplete coverage for this region. The version of the GIDD model used in this study includes household survey data for Yemen and Syria only, while large economies from the region, such as Bahrain, Qatar, UAE, Israel or Iran, are not covered in the model.

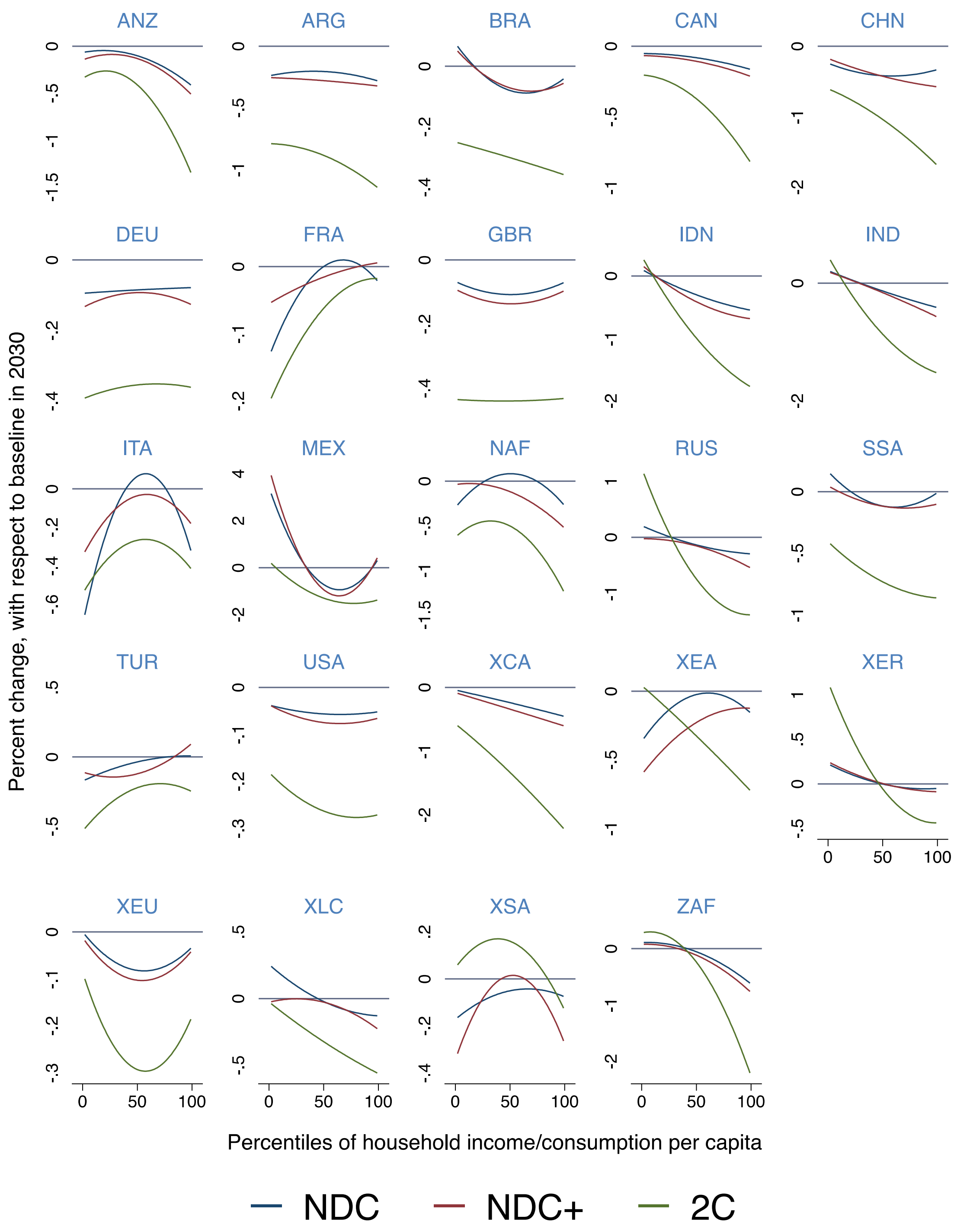

Figure 9. Growth Incidence Curves under the "Global" cooperation
Source: estimated by authors.
Notes: Results for the "MET" region are not reported, due to the unreliable survey data and incomplete coverage for this region. The version of the GIDD model used in this study includes household survey data for Yemen and Syria only, while large economies from the region, such as Bahrain, Qatar, UAE, Israel or Iran, are not covered in the model.

One non-intuitive result from the assessment of the global inequality measures is an increase in inequality under GE(2) indicator for NDC mitigation effort and “REF” cooperation, while GE(0) and GE(1) point to a decline in inequality under the same policy set up. This result suggests that when more weight is given to changes that occur at the top of the distribution, a moderate increase in inequality is observed. This implies that under NDC mitigation effort and “REF” cooperation, the net effect on inequality would depend on the judgment about the importance given to changes in certain parts of the distribution. This ambiguous result from the more modest of all scenarios does not occur under the more ambitious mitigation efforts or when the “Global” cooperation is considered (Table 5). Therefore, our results provide a strong support for a decline in global inequality under a broad set of the climate mitigation scenarios.

5. Summary and conclusions

While pursuing of a more stringent climate mitigation effort is needed to keep the global warming below 2^{o}C, as desired by the Paris Climate Agreement, such actions are associated with significant implementation costs and could impact different dimensions of human well-being, including welfare, poverty and distributional aspects. Several studies have shown that carbon taxation could result in regressive distributional impacts for households and that the properly designed compensatory measures should be implemented to avoid such regressive outcomes (Ohlendorf et al., 2018; Haug et al., 2018).

Available literature suggests mixed implications on poverty and inequality. Dorband et al. (2019) find progressive income impacts for the low-income countries and mostly regressive for the middle-income economies. Meta-analysis by Ohlendorf et al. (2018) also suggests mostly progressive impacts in lower income countries. Some studies support the point of the regressive implications of the economy-wide CO_2 prices or increasing cost of energy in the high-income countries (e.g. Ekins et al., 2011; Frondel et al., 2015; Wier et al., 2005), while other report progressive impacts (e.g. Montenergo et al., 2019). Results for the developing countries are even more diverse (Nurdianto and Resosudarmo, 2016; Vandyck and Van Regemorter, 2014; Yusuf, 2008).

Reporting numerous cases of country and region-specific climate policy incidence assessments, the literature lacks an analysis of distributional impacts of the climate mitigation policies consistent with the active international commitments, such as the NDCs, and implemented at a multi-region scale. To fill this gap, in this paper, we have analyzed the poverty and distributional impacts of different carbon pricing mechanisms consistent with reaching the NDC targets. For this analysis, we have linked a dynamic CGE model ENVISAGE (van der Mensbrugghe, 2019) with the GIDD microsimulation model (Bussolo et al., 2010). Two baseline scenarios with energy and emission profiles based on the International and World Energy Outlooks are considered. Three policy scenarios are further imposed on top of the baseline pathways – NDC (consistent with unconditional NDC targets), NDC+ (consistent with conditional NDC targets) and NDC-2C (consistent with a 2^{o}C pathway). In addition, five different carbon pricing options are considered within the assessment, including a no trade scenario, global trade in CO_2 and several options of partial sectoral and/or regional trade coalitions.

Results suggest that at the inter-regional level carbon pricing policies lead to a moderate reductions in welfare, as global welfare falls by between 0.4% and 1.4% depending on the mitigation effort (under the “REF” cooperation case). Implementation of the “ASIA” ETS does not have any substantial impact on the global welfare, bringing on average 0.9% lower welfare loss than under the "REF" case (average over baselines and mitigation scenarios). "PARTIAL" and "EU-CHN" cooperation scenarios lower global welfare losses by around 10% (relative to the "REF" case). Switching from the regional action ("REF" scenario) to global cooperation ("GLOBAL") reduces welfare loss on average a factor of 2.5.

At the regional level, Russia, Rest of Central Asia and Saudi Arabia are among the most impacted regions, with welfare reductions of around 1.5%, "NDC" mitigation scenario and "REF" collaboration case (Table G.1, Appendix G). In the case of 2°C-consistent scenario, welfare in Saudi Arabia falls by around 8.5%, followed by Rest of Central Asia (-6%), Middle Eastern countries (-3.8%) and Russia (-3.3%). All four regions include large energy exports, suffering from the reduction in global energy prices and deteriorating terms of trade effects. In particular, the reduction in prices of fossil fuel exports for these countries range between 4.3% for the Rest of Central Asia to 7.6% for Russia (under "REF" cooperation scenario and "NDC-2C" mitigation case). It should be noted that not all energy exporters are among the most impacted regions. For instance, Canada, which is a large oil exporter, experiences lower reductions in welfare (-1.7%) compared to the other regions discussed above. One particular reason for such difference is that Canadian export basket is much more diversified (with the share of fossil fuels around 17% in total exports and 4.5% share in GDP),[16] while economies of both Russia and to a large extent Saudi Arabia are much more dependent on the exports of fossil fuel. In the case of Russia fossil fuels constitute 59.6% of exports and 13.1% of GDP, while for Saudi Arabia these shares are even higher – 85.7% and 49.1% respectively. In the case of Saudi Arabia, negative impacts of the climate mitigation policies are further increased by the fact that the share of renewable generation technologies is "0" (under both baseline and policy scenarios), therefore the cost of mitigation policies for this country is relatively high.

There is a moderate trend towards regressive distribution of the welfare impacts by regions, as countries with lower per capita real income tend to face somewhat higher reductions in welfare. "GLOBAL" cooperation results in a less regressive inter-regional welfare distribution. Nevertheless, observed welfare outcomes still support the need of financial transfers from richer to poorer countries to make the climate mitigation costs distribution more uniform under the case of global cooperation.

At the intra-regional level, results suggest that while there is a higher incidence of poverty in all scenarios, mainly driven by lower economic growth, NDC policies result in progressive income distribution at the global level. Such progressivity is caused not only by lower relative prices of food versus non-food commodities, but also by a general decline in skill wage premia. Achievement of the NDC targets without regional cooperation results in 0.45% increase in the number of people living in extreme poverty (below PPP$1.90/day) by 2030, while a more ambitious 2C-consistent target increases this number to 1.25%. In absolute terms, these scenarios correspond to the increase in poverty headcount by 2.9 and 7.9 million people respectively.

"GLOBAL" cooperation significantly eases the burden on poor, reducing the poverty headcount (additional number of people leaving in extreme poverty) by almost three times in the case of 2C-consistent target (2.9 million people increase in poverty headcount relative to the baseline). In the case of "GLOBAL" cooperation under NDC target poverty headcount remains unchanged relative to the baseline scenario level.

[16] These shares are reported for the 2011 reference year.

Progressivity of income distribution at the global level is supported by several inequality indices that differ in their sensitivities to income differences in different parts of the distribution. Global Gini coefficient falls between 0.01 and 0.04 percentage points depending on the mitigation effort and collaboration mode, while reduction in the Theil index is between 0.01 and 0.11 percentage points. Results also indicate that the reductions in inequality come mainly from reduction in income from top earners, as the results are much more sensitive to the NDC policies closer to the top of the income distribution. Almost all regions show progressive income distribution under both "REF" and "GLOBAL" cooperation arrangements, though France and Turkey are the only exceptions in both cases, showing some regressivity of carbon pricing impacts.

Combination of the income side effects – reduction in wage skill premia – and expenditure side effects – relative reduction in food prices and high share of food expenditures for low-income households in developing countries – results in the fact that in some developing countries even under the ambitious climate mitigation efforts (e.g. consistent with 2°C), real income of the lowest percentiles increases. For instance, this is the case for Indonesia, India, Mexico, Rest of Europe, Rest of East Asia and Rest of South Asia. This result has important policy implications in that while climate change is found to have a significant adverse impacts on low income households in developing countries (e.g. Mideksa, 2010; Ibarraran et al., 2009), climate mitigation policies not only could reduce those impacts, but also benefit some of the poorest households in selected regions, thus providing governments of these countries an additional motivation to participate in the global mitigation efforts.

Using the global macro-micro simulations model linkage and providing new insights on the assessment of inter- and intra-regional impacts of NDC-consistent policies, our analysis is not without limitations and need for further extensions. *First,* while representing over 82.7% of global GDP and 85.4% of global population, the GIDD microsimulation modelling framework still misses some important countries, explicitly represented in the CGE model, such as Korea, Japan and Saudi Arabia. Some regions, such as Middle East and North Africa have a relatively low representation in GIDD (21% of GDP in the case of MENA countries). Adding these data to the microsimulation framework would help to provide a better global coverage. *Second,* several improvements can be implemented in terms of the ENVISAGE-GIDD model linkage. These include data exchange at a more disaggregate sectoral level (compare to the current food/non-food and agricultural/non-agricultural splits), as well as introduction of a two-way data exchange between model, where some indicators from GIDD would be transferred back to the ENVISAGE for refinement of the policy assessment (see e.g. Savard, 2003; Giulia, 2008). *Third,* both more ambitious and longer-term climate mitigation efforts could be analyzed, i.e. targets consistent with 1.5°C 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.[17] *Fourth,* while focusing on the mid-term time horizon—till 2030, we have not introduced climate change impacts into the general framework. If a longer-term timeframe is considered, taking these interactions into account would be an important addition to the implemented framework. *Finally,* within the current assessment we have not explored the question of transfer payments and compensations, both between countries and by household groups.

[17] Comparison between NDC and NDC-2C mitigation pathways indicates moderate non-linearity of impacts with increasing mitigation effort. While between NDC and NDC-2C scenarios global mitigation effort relative to baseline level in 2030 increases by 2.8 times (from -9.6% under NDC to -27% under NDC-2C) welfare reduces by 3.3 times (from -0.35% under NDC to -1.16% under NDC-2C).

Different carbon revenue recycling options (reduction in labor or production taxes, subsidy to renewables, etc.) could also result in different incidence effects (in this paper we have only considered the option of lump-sum payment to the representative regional household). Exploring these various set ups of the carbon revenue redistribution could further enrich the analysis and provide additional insights.

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Appendix A. Overview of the ENVISAGE model nesting structures and core elasticities

Figures in this appendix describe some selected nesting structures relevant for the current paper. Values of the corresponding elasticities are reported in the Table D.1. A more detailed discussion of the ENVISAGE model can be found in van der Mensbrugghe (2019).

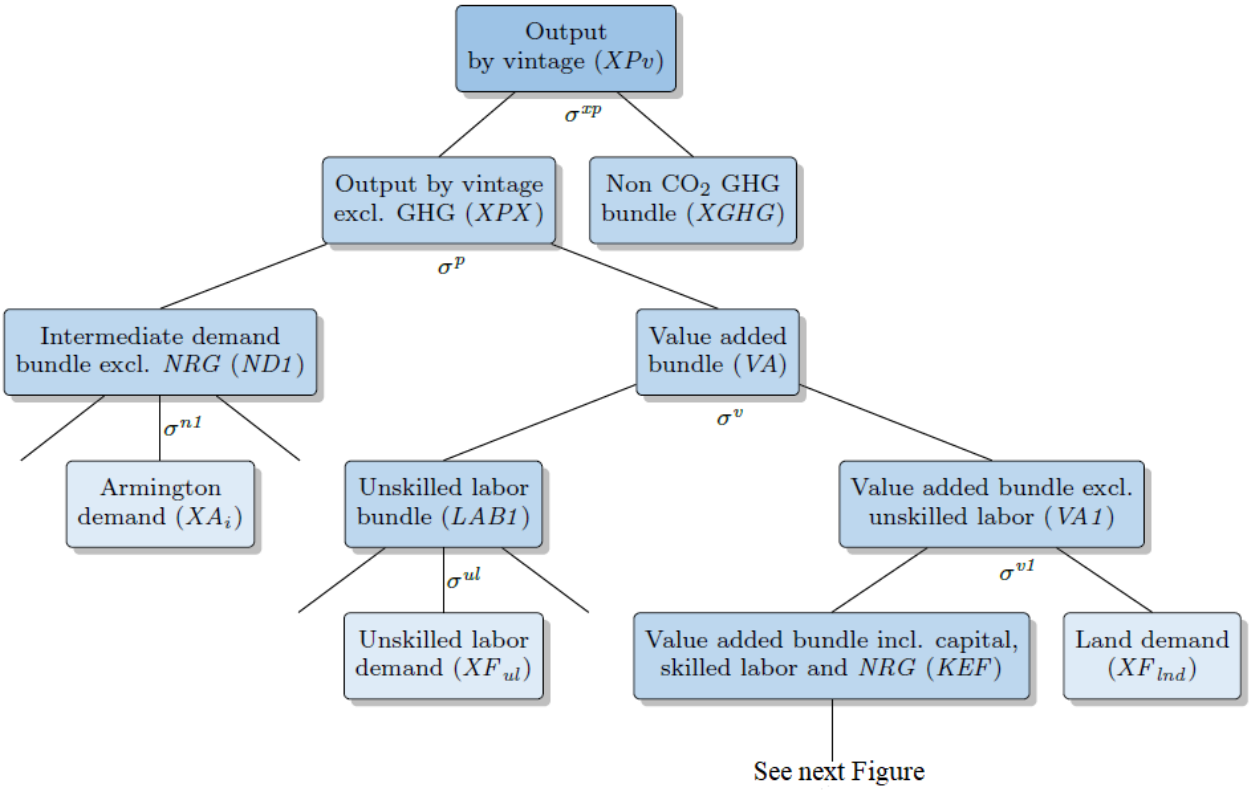

Figure A.1. Default production nest

Source: authors.

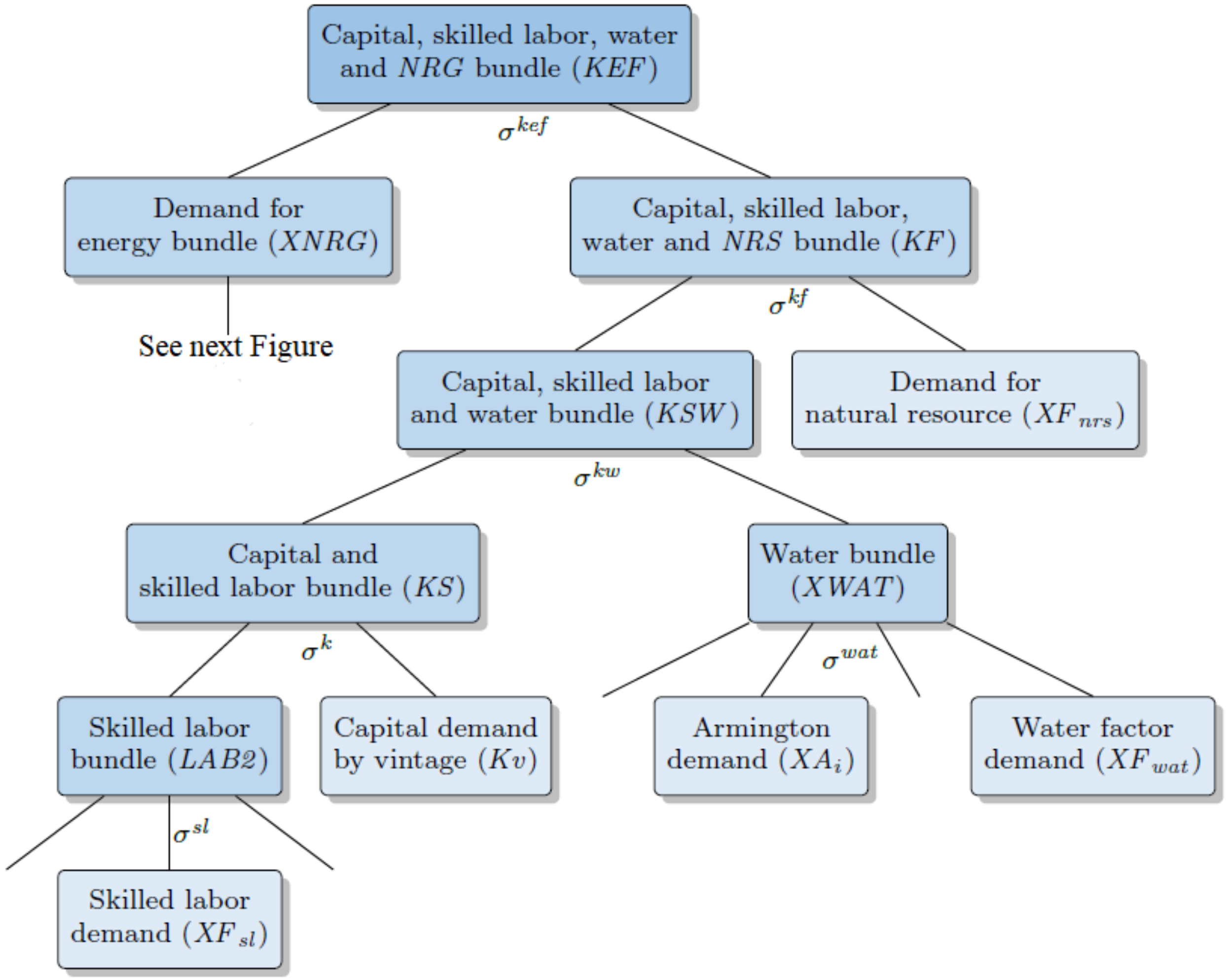

Figure A.2. Capital-energy-production factors (KEF) bundle nest
Source: authors.
Notes: we do not include explicit representation of the water flows within the current exercise, though such capability is available in the model.

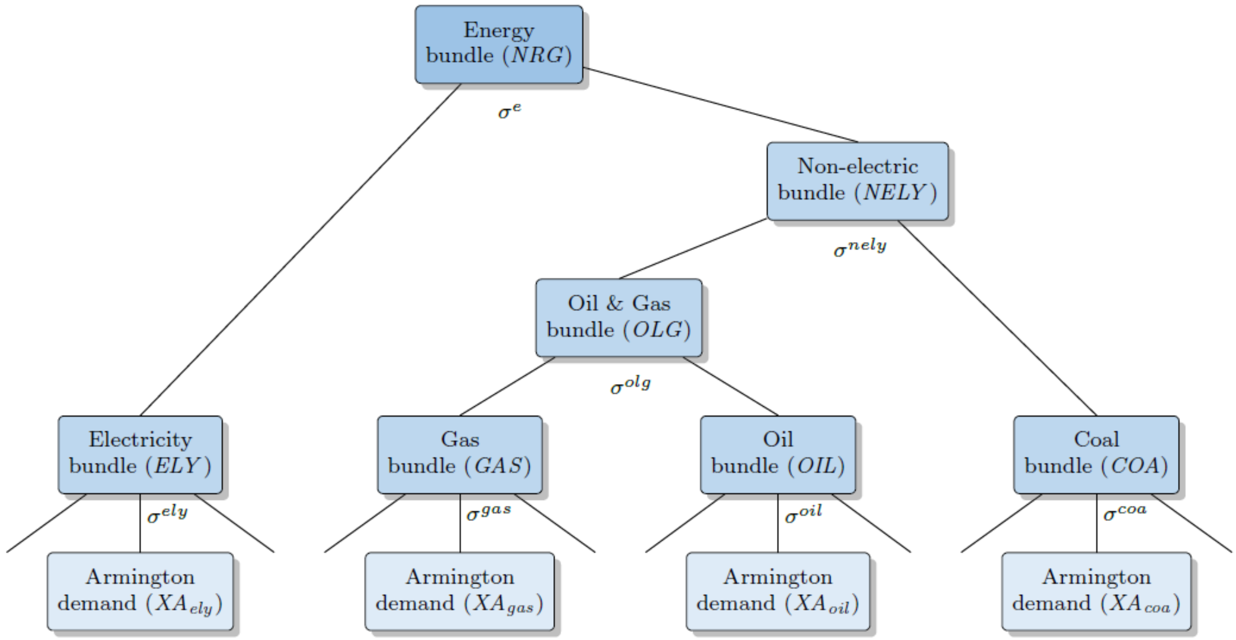

Figure A.3. Energy bundle nest
Source: authors.

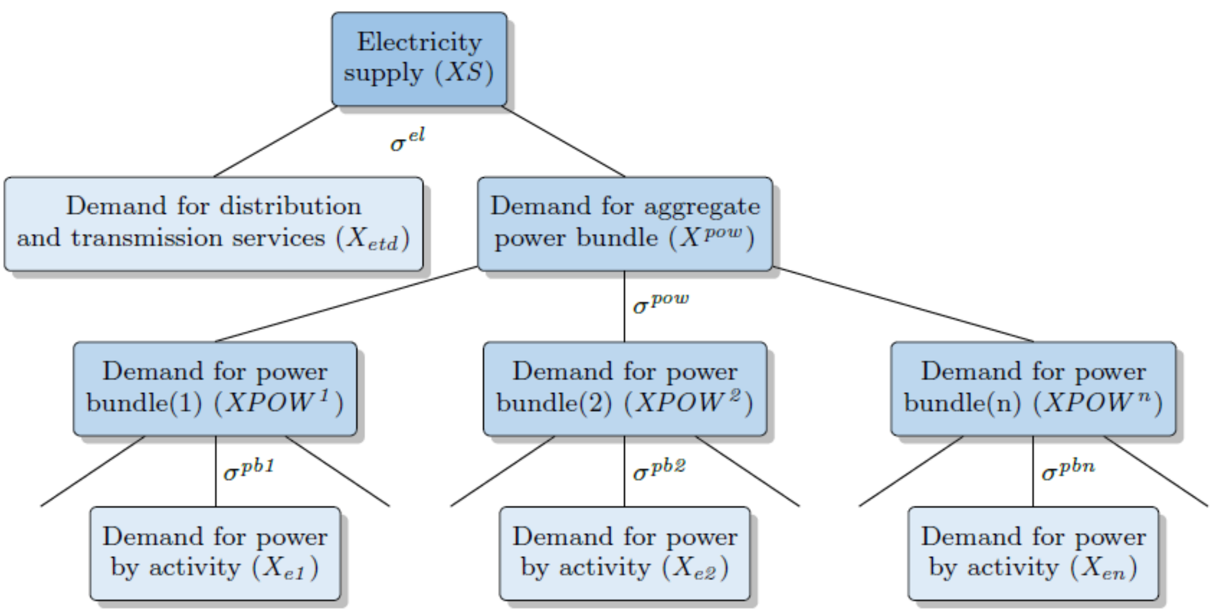

Figure A.4. CES nest for power bundle
Source: authors.
Notes: we use five power bundles for the EMF36 exercise; they include gas power, oil power, coal power, nuclear, hydro and renewables; all bundles include single generation technology, except for renewable bundle, the latter one consists of wind, solar and other renewable generation technologies.

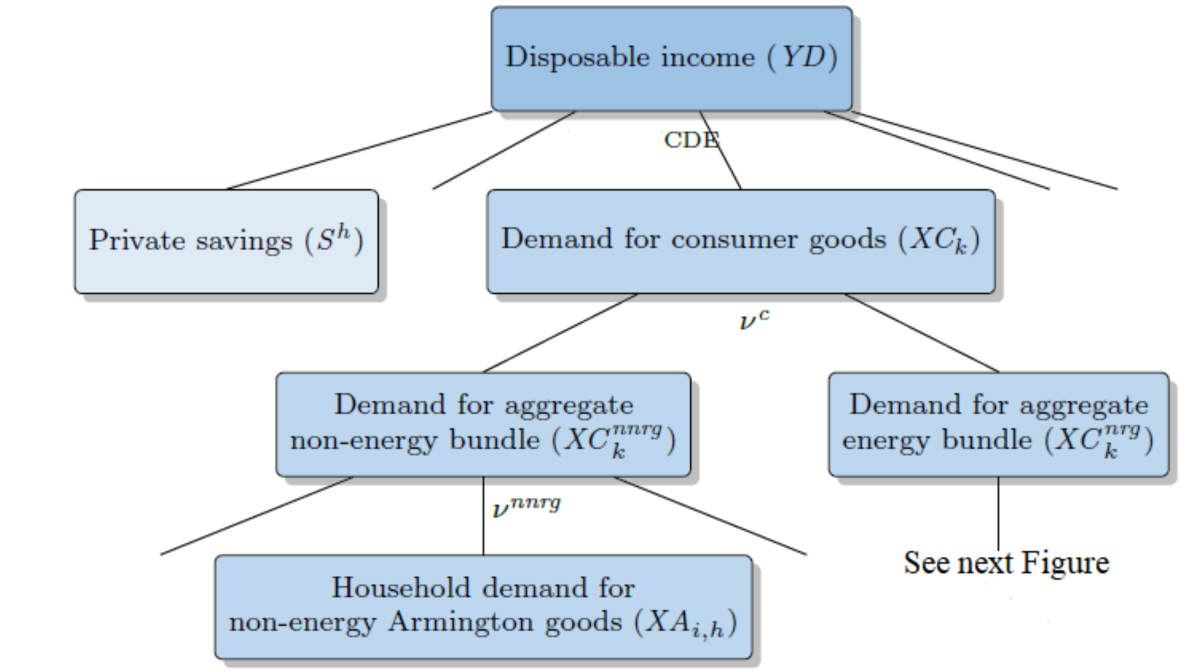

Figure A.5. Consumer demand nest
Source: authors.

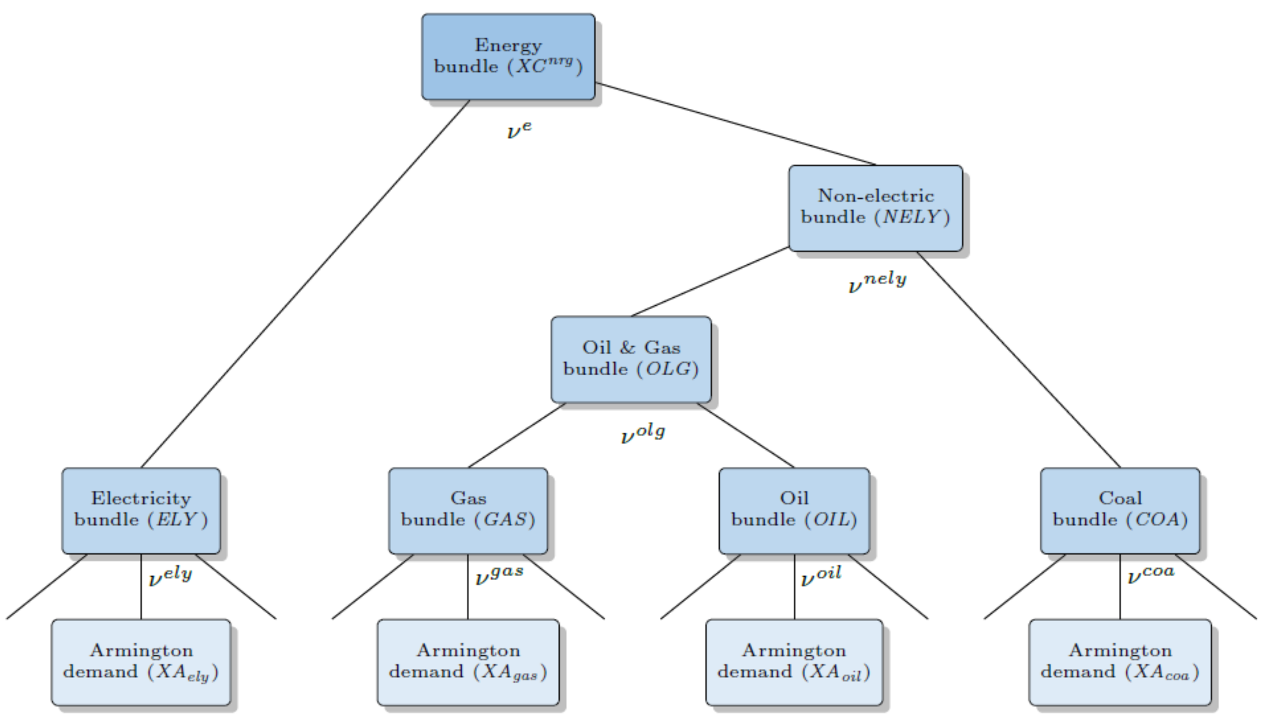

Figure A.6. Energy bundle nest in household demand
Source: authors.

Table A.1. Values of the key elasticities in the ENVISAGE model

Elasticity	Description	Value
σ^{xp}	CES between GHG and XP. Non-CO_2 GHGs are not included into current assessment	NA
σ^{p}	CES between ND1 and VA	0.0
σ^{n1}	CES across intermediate demand in ND1 bundle	0.0
σ^{v}	CES between LAB1 and VA1 in crops and other, VA1 and VA2 in livestock. Differentiated by vintages.	0.12 – old 1.01 – new
σ^{ul}	CES across unskilled labor	0.5
σ^{v1}	CES between ND2 (fert) and VA2 in crops, LAB1 and KEF in livestock and land and KEF in other (by vintages)	0.12 – old 1.01 – new
σ^{kef}	CES between KF and NRG (by vintages)	0.8 – new
σ^{kf}	CES between KSW and NRF (by vintages)	0.25 – old 0.25 – new
σ^{kw}	CES between KS and XWAT (by vintages)	0.1
σ^{k}	CES between LAB2 and K (by vintages)	0.12 – old 1.01 – new
σ^{wat}	CES across intermediate demand in WAT bundle	0.0
σ^{sl}	CES across skilled labor	0.5
σ^{e}	CES between ELY and NELY in energy bundle (by vintages)	0.25 – old 2.0 – new
σ^{nely}	CES between COA and OLG in energy bundle (by vintages)	0.25 – old 2.0 – new
σ^{olg}	CES between OIL and GAS in energy bundle	0.25 – old 2.0 – new
σ^{ely}	CES within ely bundle (by vintages)	0.25 – old 2.0 – new
σ^{gas}	CES within gas bundle (by vintages)	0.25 – old 2.0 – new
σ^{oil}	CES within oil bundle (by vintages)	0.25 – old 2.0 – new
σ^{coa}	CES within coa bundle (by vintages)	0.25 – old 2.0 – new
σ^{el}	Substitution between power and distribution and transmission	0.0
σ^{pow}	Substitution across power bundles	1.2
σ^{pb}	Substitution across power activities within power bundles	1.2

Source: authors.

Appendix B. Regional coverage

Table B.1. Mapping between modelled and GTAP 9.2 regions

No.	Aggregate region		GTAP 9.2 region
1.	United States (USA)	United States (USA)	United States (USA)
2.	Canada (CAN)	Canada (CAN)	Canada (CAN)
3.	Japan (JPN)	Japan (JPN)	Japan (JPN)
4.	South Korea (KOR)	South Korea (KOR)	South Korea (KOR)
5.	Russia (RUS)	Russia (RUS)	Russia (RUS)
6.	China, P.R. (CHN)	China, P.R. (CHN)	China (CHN), Hong Kong (HKG)
7.	India (IND)	India (IND)	India (IND)
8.	Australia and New Zealand (ANZ)	Australia and New Zealand (ANZ)	Australia (AUS), New Zealand (NZL)
9.	Brazil (BRA)	Brazil (BRA)	Brazil (BRA)
10.	Argentina (ARG)	Other Americas (OAM)	Argentina (ARG)
11.	France (FRA)	Europe (EUR)	France (FRA)
12.	Germany (DEU)	Europe (EUR)	Germany (DEU)
13.	Italy (ITA)	Europe (EUR)	Italy (ITA)
14.	United Kingdom (GBR)	Europe (EUR)	United Kingdom (GBR)
15.	Indonesia (IDN)	Other Asia (OAS)	Indonesia (IDN)
16.	Mexico (MEX)	Other Americas (OAM)	Mexico (MEX)
17.	Saudi Arabia (SAU)	Middle East (MEA)	Saudi Arabia (SAU)
18.	South Africa (ZAF)	Africa (AFR)	South Africa (ZAF)
19.	Turkey (TUR)	Middle East (MEA)	Turkey (TUR)
20.	Rest of EU and EFTA (XEU)	Europe (EUR)	Austria (AUT), Belgium (BEL), Bulgaria (BGR), Croatia (CRO), Cyprus (CYP), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), Greece (GRC), Hungary (HUN), Ireland (IRL), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), Switzerland (CHE), Norway (NOR), Rest of EFTA (XEF)
21.	Rest of Europe (XER)	Europe (EUR)	Albania (ALB), Belarus (BLR), Ukraine (UKR), Rest of Eastern Europe (XEE), Rest of Europe (XER)
22.	Rest of Central Asia (XCA)	Other Asia (OAS)	Kyrgyzstan (KGZ), Tajikistan (TJK), Rest of Former Soviet Union (XSU), Armenia (ARM), Georgia (GEO), Kazakhstan (KAZ), Azerbaijan (AZE)
23.	Rest of East Asia (XEA)	Other Asia (OAS)	Rest of Oceania (XOC), Mongolia (MNG), Rest of East Asia (XEA), Brunei Darussalam (BRN), Cambodia (KHM), Laos (LAO), Malaysia (MYS), Philippines (PHL), Thailand (THA), Viet Nam (VNM), Rest of Southeast Asia (XSE), Taiwan (TWN), Singapore (SGP), Rest of the World (XTW)
24.	Rest of South Asia (XSA)	Other Asia (OAS)	Bangladesh (BGD), Nepal (NPL), Pakistan (PAK), Sri Lanka (LKA), Rest of South Asia (XSA)

No.	Aggregate region		GTAP 9.2 region
25.	Middle East (MET)	Middle East (MEA)	Bahrain (BHR), Iran (IRN), Kuwait (KWT), Oman (OMN), Jordan (JOR), Qatar (QAT), United Arab Emirates (ARE), Rest of Western Asia (XWS), Israel (ISR)
26.	North Africa (NAF)	Africa (AFR)	Rest of North Africa (XNF), Egypt (EGY), Morocco (MAR), Tunisia (TUN)
27.	Sub-Saharan Africa (SSA)	Africa (AFR)	Benin (BEN), Burkina Faso (BFA), Cameroon (CMR), Côte d'Ivoire (CIV), Ghana (GHA), Guinea (GIN), Nigeria (NGA), Senegal (SEN), Togo (TGO), Rest of Western Africa (XWF), Central Africa (XCF), South-Central Africa (XAC), Ethiopia (ETH), Kenya (KEN), Madagascar (MDG), Malawi (MWI), Mauritius (MUS), Mozambique (MOZ), Rwanda (RWA), Tanzania (TZA), Uganda (UGA), Zambia (ZMB), Zimbabwe (ZWE), Rest of Eastern Africa (XEC), Botswana (BWA), Namibia (NAM), Rest of South African Customs Union (XSC)
28.	Rest of Latin America, Caribbean and Rest of North America (XLC)	Other Americas (OAM)	Bolivia (BOL), Colombia (COL), Ecuador (ECU), Venezuela (VEN), Chile (CHL), Paraguay (PRY), Peru (PER), Uruguay (URY), Rest of South America (XSM), Costa Rica (CRI), Guatemala (GTM), Honduras (HND), Nicaragua (NIC), Panama (PAN), El Salvador (SLV), Rest of Central America (XCA), Dominican Republic (DOM), Jamaica (JAM), Puerto Rico (PRI), Trinidad and Tobago (TTO), Rest of Caribbean (XCB), Rest of North America (XNA)

Source: authors.

Appendix C. Sectoral coverage

Table C.1. Mapping between modelled and GTAP-Power 9.2 sectors

No.	Sector code	Sector description	GTAP-Power 9.2 sector
1.	ric	Rice	pdr pcr
2.	wht	Wheat	wht
3.	gro	Other cereal grains and their products	gro
4.	osd	Oil seeds	osd
5.	sug	Sugar	c_b sgr
6.	ocr	Other crops	v_f pfb ocr
7.	lvs	Livestock	ctl oap rmk wol
8.	frs	Forestry	frs
9.	coa	Coal	coa
10.	oil	Oil	oil
11.	gas	Gas	gas gdt
12.	omn*	Minerals nec	omn
13.	vol	Vegetable oils and fats	vol
14.	mil	Dairy products	mil
15.	mtp	Meat products	cmt omt fsh
16.	xfd	Other food products	ofd b_t
17.	xma	Other manufacturing	tex wap lea lum mvh otn ele ome omf fmp
18.	p_c	Petroleum and coal products	p_c
19.	eit*	Energy intensive goods	crp nmm i_s nfm ppp
20.	etd	Electricity transmission	TnD
21.	nuc*	Nuclear power	NuclearBL
	clp*	Coal-fired power	CoalBL
22.	gsp*	Gas-fired power	GasBL GasP
23.	wnd*	Wind power	WindBL
24.	hyd*	Hydro power	HydroBL HydroP
25.	olp*	Oil-fired power	OilBL OilP
26.	xel*	Other power	OtherBL
27.	sol*	Solar power	SolarP
28.	trn	Transportation	otp wtp atp
29.	srv	Services	wtr trd cns cmn ofi isr obs ros osg dwe

Source: authors.

Note: for the complete list and description of GTAP-Power 9.2 sectors see Peters (2016a). "*" indicates energy intensive and trade exposed (EITE) sectors.

Appendix D. Baseline assumptions

Table D.1. Selected baseline assumptions for the ENVISAGE model

Assumption	Implementation	Specific assumptions
Costs of renewables are declining over time	The cost reduction is implemented using a hyperbolic specification with a cost asymptote. The curve is calibrated to three parameters – the asymptote (relative to current costs), a targeted reduction and the year the target is reached.	Wind – the asymptote is 80% of today's price and the costs are dropping by 10% between 2011 and 2030. Solar and other renewables – the asymptote is 60% and the costs are dropping by 20% between 2011 and 2030.
Non-price related changes in preferences towards renewables	Preference 'twist' parameters change the preference for one set of commodities in a demand system relative to other commodities, but without changing the aggregate cost (Dixon and Rimmer, 2002; van der Mensbrugghe, 2019).	We assume a target for renewable electricity as a share of total electricity demand and implement the twist assuming no change in prices (from the base year). The assumed shares are provided in Appendix D. The actual shares are likely to be higher given the decline in costs and the developments in the cost of other power activities. We do not introduce renewables, as a new technology, in case of countries with "0" renewables share in the benchmark 2011 year.
Target increase in electricity share for agents (trend towards electrification following IEA (2017a))		Region/country-specific assumption on changes in electricity shares are reported in Appendixes E and F.
Energy efficiency improvements	Improvements in energy efficiency are captured by the autonomous energy efficiency improvement parameter (AEEI). We assume AEEI to be differentiated by countries and changing over time.	In the benchmark year, AEEI is set at one per cent per annum across all activities, energy sources, and vintages (old vintage represents installed capital, while new vintage represents most recent supply of capital). AEEI values are further linked to the GDP growth rates and assume to increase with higher per capita GDP growth. For instance, if the GDP growth rate is two per cent per annum, AEEI equals one per cent per annum, while if GDP increases at the rate of eight per cent per annum, AEEI equals five per cent per annum. We use a power function with defined elasticities to establish such link between GDP growth and AEEI values and use lower (0.5%) and upper (4.5%) bounds to cap AEEI levels. Fixed AEEI values are used for coal consumption (one per cent in developing countries and 0.5% in developed). Further adjustments are used to match the BaU emissions under WEO pathway.
Improvements in international transport costs		Costs decline by one per cent per annum.
Crude oil price trends		Oil prices in both baselines follow World Energy Outlook "Current policies" scenario (IEA, 2018).

Source: authors.

Appendix E. Renewable generation share assumptions

Table E.1. Assumed shares of renewables in electricity generation in 2030 under WEO baseline, %[18]

Region	Targeted share
United States (USA)	30
Canada (CAN)	20
Japan (JPN)	35
South Korea (KOR)	15
Russia (RUS)	20
China, P.R. (CHN)	30
India (IND)	12
Australia and New Zealand (ANZ)	20
Brazil (BRA)	na
Argentina (ARG)	10
France (FRA)	11
Germany (DEU)	35
Italy (ITA)	45
United Kingdom (GBR)	30
Indonesia (IDN)	15
Mexico (MEX)	15
Saudi Arabia (SAU)[19]	na
South Africa (ZAF)	10
Turkey (TUR)	15
Rest of EU and EFTA (XEU)	35
Rest of Europe (XER)	25
Rest of Central Asia (XCA)	25
Rest of East Asia (XEA)	na
Rest of South Asia (XSA)	10
Middle East (MET)	15
North Africa (NAF)	15
Sub-Saharan Africa (SSA)	10
Rest of Latin America, Caribbean and Rest of North America (XLC)	15

Source: authors.

[18] Renewables under targeting include, wind, solar and other renewable generation.
[19] In the case of Saudi Arabia, the share of renewable generation is “0” in 2011.

Appendix F. Electricity shares targeting in the baseline

Table F.1. Target increase in electricity share in 2030 w.r.t. 2011, (2011=1)[20]

	trn-a	ric-a	wht-a	gro-a	osd-a	sug-a	ocr-a	lvs-a	frs-a	omn-a	vol-a	mil-a	mtp-a	xfd-a	xma-a	eit-a	srv-a
USA	1.5	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
CAN	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
JPN	1.3	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
KOR	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
RUS	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
CHN	1.5	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2
IND	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
ANZ	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
BRA	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
ARG	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
FRA	1.6	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.5
DEU	1.4	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2
ITA	1.5	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
GBR	1.4	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.2
IDN	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
MEX	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
SAU	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
ZAF	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
TUR	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
XEU	1.5	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3
XER	1.5	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
XCA	1.5	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.4
XEA	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
XSA	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
MET	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
NAF	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
SSA	1.3	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
XLC	1.2	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1

Source: authors.

[20] E.g. "1.5" in the (USA, trn-a) cell stands for the 1.5 times increase in electricity share for transportation activity in 2030 w.r.t. 2011. For instance, if the share of electricity, as the energy source, in transportation was 2% in 2011, then the target is 3% in 2030.

Appendix G. Additional indicators of the carbon pricing policy assessment

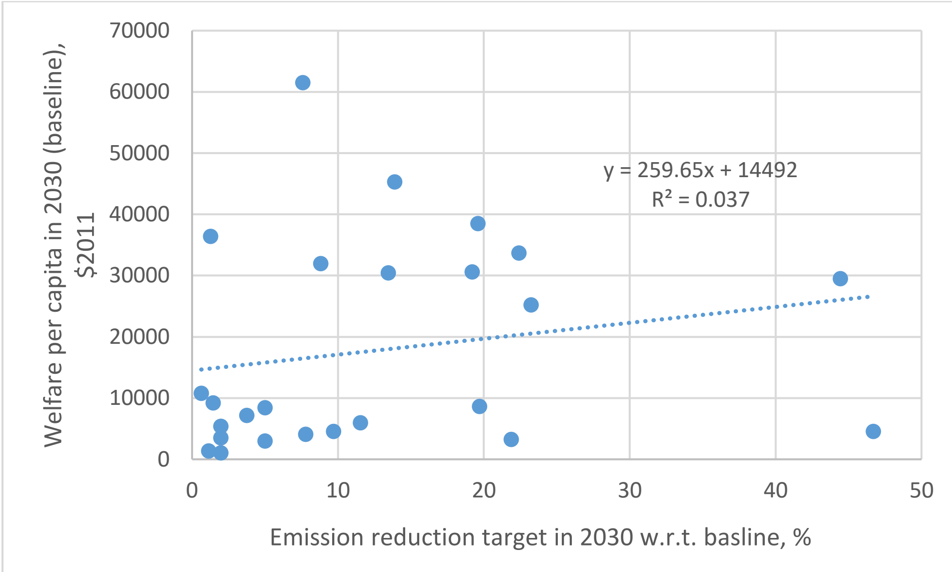

Figure G.1. Emission reduction targets under "NDC" scenario vs per capita welfare in the baseline scenario in 2030

Source: estimated by authors.

Notes: each point represents one of the 28 regions (see Appendix B for the list of regions).

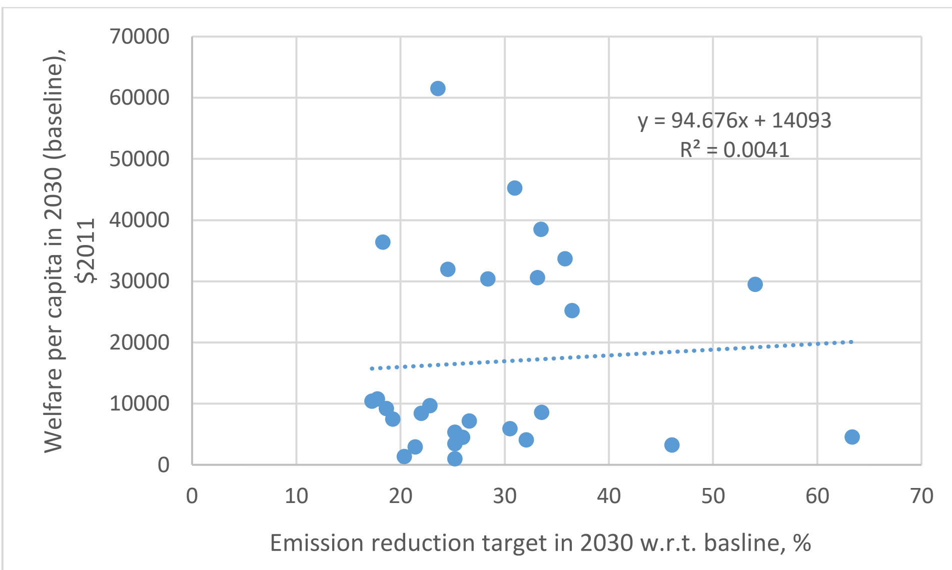

Figure G.2. Emission reduction targets under "NDC-2C" scenario vs per capita welfare in the baseline scenario in 2030

Source: estimated by authors.

Notes: each point represents one of the 28 regions (see Appendix B for the list of regions).

Table G.1. Impacts on welfare, % change in 2030 relative to baseline

Reduction target	NDC		NDC+		NDC-2C	
Region\cooperation	**ref**	**global**	**ref**	**global**	**ref**	**global**
USA	-0.18	-0.06	-0.23	-0.07	-0.58	-0.27
CAN	-0.61	-0.12	-0.66	-0.16	-1.69	-0.61
JPN	-0.06	-0.06	-0.06	-0.08	-0.64	-0.27
KOR	0.41	0.02	0.39	0.02	0.04	0.07
RUS	-1.53	-0.26	-1.60	-0.34	-3.31	-1.18
CHN	-0.21	-0.44	-0.24	-0.56	-0.8	-1.46
IND	-0.06	-0.26	0.01	-0.35	-0.4	-1.18
ANZ	-0.47	-0.22	-0.56	-0.28	-1.47	-0.78
BRA	-0.58	-0.07	-0.62	-0.09	-1.85	-0.34
eur	-0.48	-0.06	-0.48	-0.08	-1.16	-0.28
mea	-0.82	-0.38	-1.21	-0.5	-3.51	-1.84
afr	-0.73	-0.20	-0.93	-0.26	-2.37	-1.01
oam	-0.35	-0.18	-0.48	-0.24	-1.59	-0.86
oas	-1.56	-0.21	-2.84	-0.27	-5.54	-0.81
World	**-0.41**	**-0.17**	**-0.53**	**-0.23**	**-1.37**	**-0.70**

Source: estimated by authors.

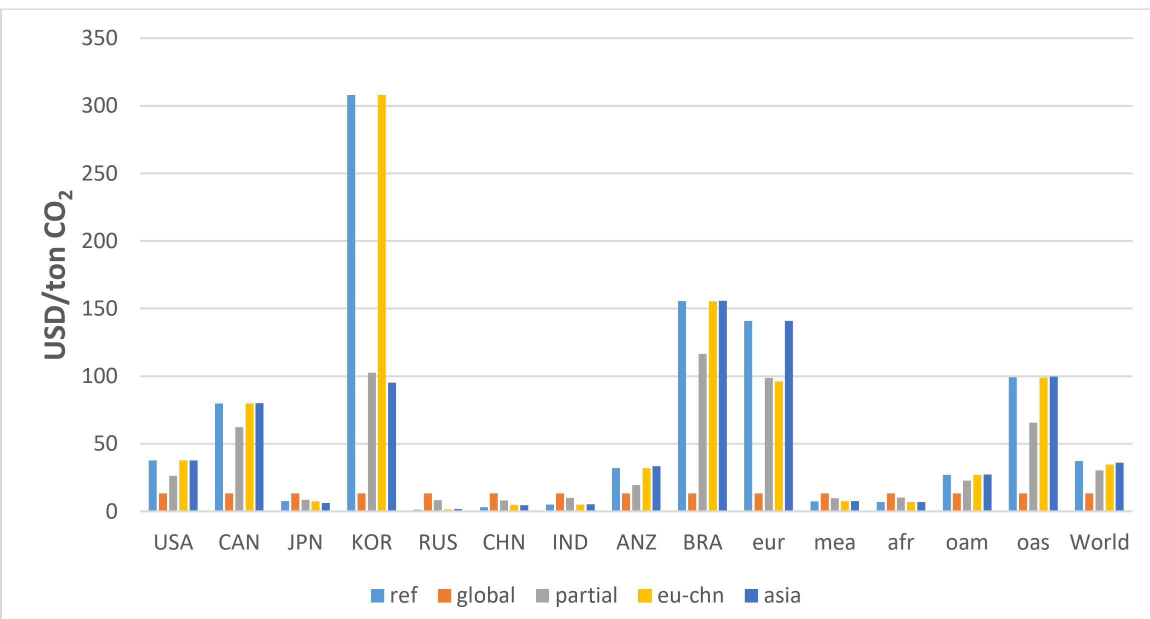

Figure G.3. Weighted average carbon prices in 2030 under "NDC" scenario and WEO baseline, \$2011/tCO_2-eq.

Source: Estimated by authors.

Notes: Carbon price is reported per metric ton (1 metric ton = 1000 kg).

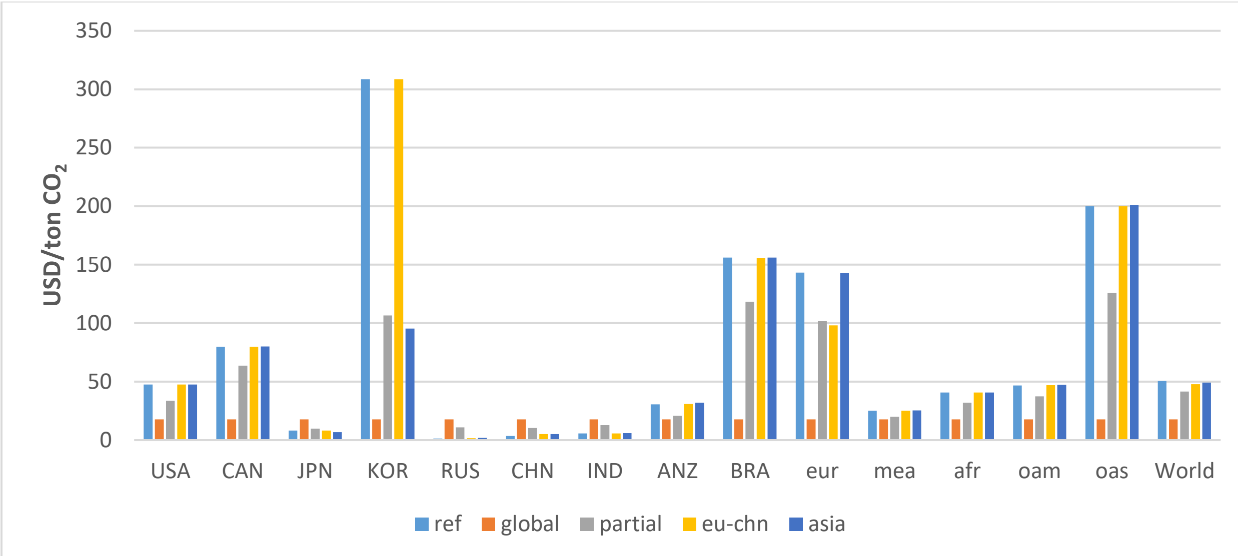

Figure G.4. Weighted average carbon prices in 2030 under "NDC+" scenario, \$2011/tCO_2-eq.

Source: estimated by authors.

Notes: Carbon price is reported per metric ton (1 metric ton = 1000 kg).

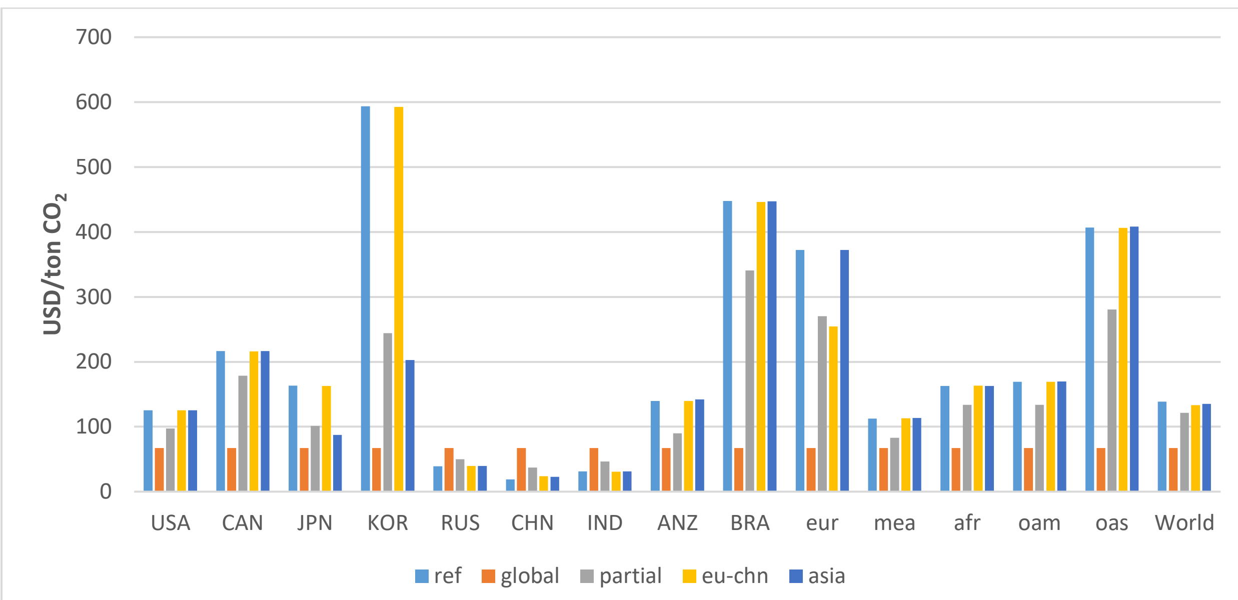

Figure G.5. Weighted average carbon prices in 2030 under "NDC-2C" scenario, \$2011/tCO_2-eq.

Source: estimated by authors.

Notes: Carbon price is reported per metric ton (1 metric ton = 1000 kg).

Appendix H. Changes in the consumer price index under "GBL" cooperation

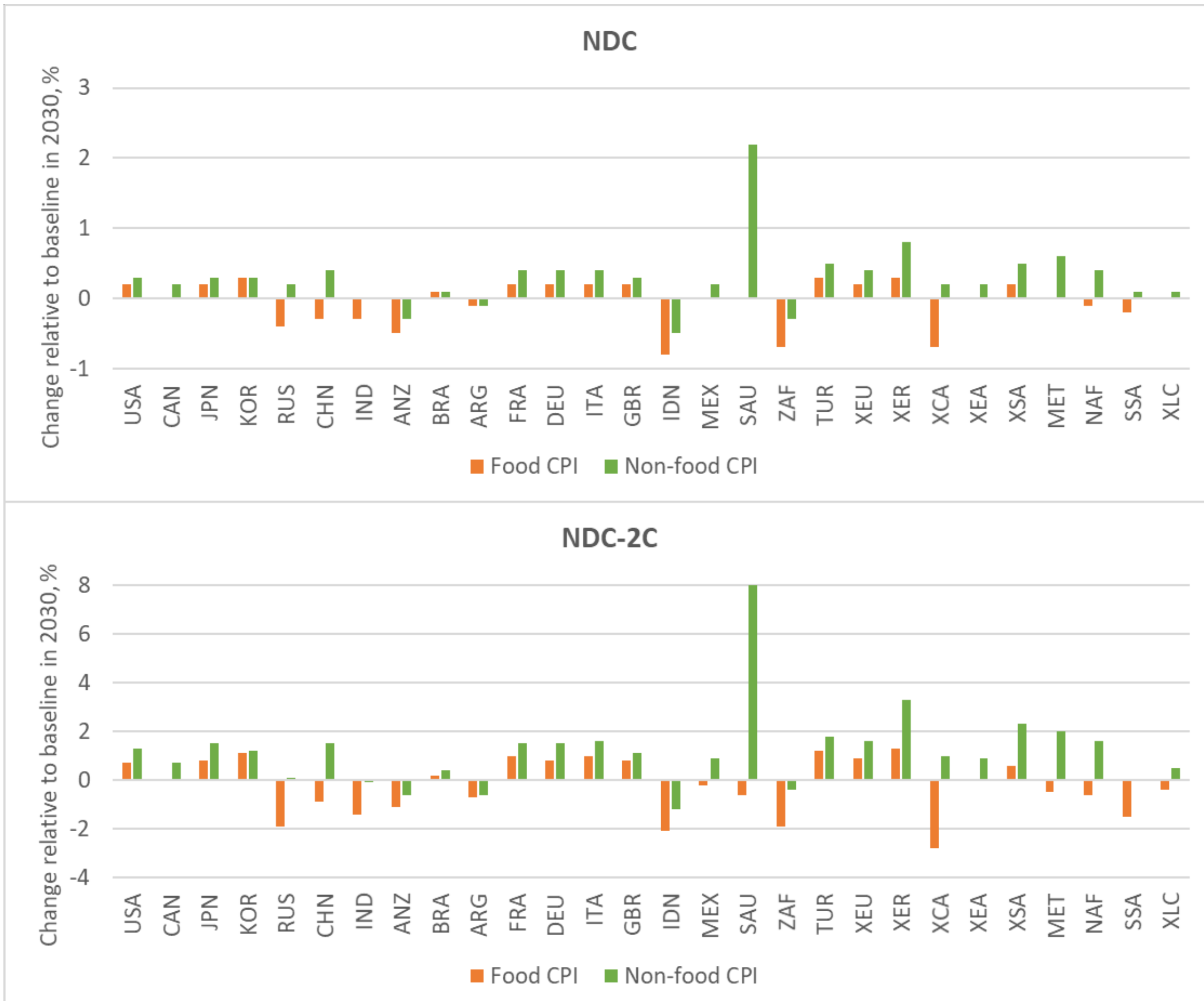

Figure H.1. Changes in the food and non-food CPI under NDC and NDC-2C emission reduction targets and "GBL" collaboration

Source: estimated by authors.

Appendix I. Household budget shares spent of food and beverages in 2011

Region	Average share, %	Income quintiles				
		I	II	III	IV	V
ANZ	12.7	16.2	13.1	12.3	11.5	10.3
ARG	30.2	38.6	32.5	29.5	27	23.4
BRA	18.2	30.3	19	16.6	14.5	10.8
CAN	11.3	18.2	11.9	9.8	8.8	7.8
CHN	26	31.3	28.5	26.3	23.8	20.3
DEU	12.9	15.2	13.6	12.8	12.1	10.9
FRA	15.9	18.3	16.7	15.8	14.9	13.6
GBR	10.9	13.1	11.5	10.8	10.2	9.1
IDN	46.4	57.9	51.6	47.2	42.3	32.8
IND	32.8	40	36.1	33.6	30.4	24
ITA	17.1	20.6	17.9	16.8	15.8	14.3
MET	43.8	54	47.5	43.9	40.3	33.3
MEX	27.9	38.6	32.2	28.2	24.2	16.5
NAF	45.3	53.4	48.4	45.5	42.6	36.5
RUS	31.3	39.1	34.5	31.7	28.7	22.6
SSA	48.3	57.1	51.6	48.6	45.6	38.6
TUR	28.3	39.4	32.6	28.1	24	17.7
USA	7.7	10.2	8.2	7.4	6.8	5.9
XCA	40.9	48.9	43.5	40.8	38	33.4
XEA	39.1	53.1	44.8	39.7	34.1	24
XER	38.8	43.5	40.4	38.8	37.1	34.3
XEU	18.8	23.6	20.1	18.6	17.1	14.7
XLC	28.3	38	31.2	27.9	24.7	19.5
XSA	54.4	65.1	58.2	55	51.5	42.2
ZAF	22.8	33.5	26.5	22.4	19	12.6

Source: developed by authors based on GIDD database.
Notes: The household surveys in the GIDD model contain either observed or estimated household budget shares for 2 broad categories of goods: food and non-food items. Coverage in terms of budget surveys varies by region and country. To complement budget shares the estimation method follows a global Engel curve approach as in de Hoyos and Lessem (2008). This method has been updated with a larger sample of countries, updates on the International Comparison Program (ICP) and harmonization from the World Bank Global Consumption Database.[21]

[21] https://datatopics.worldbank.org/consumption/

Appendix J. Overview of the selected poverty 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 $k = 1,...,K$.

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

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

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

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

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.