The Global Consumer Incidence of Carbon Pricing:

Evidence from Trade

Lutz Sager*
Georgetown University

March 11, 2022

Abstract: Carbon pricing is often seen as regressive, disproportionately burdening low-income consumers. I show that higher prices following a global carbon price would be mildly regressive in industrialized countries, mildly progressive in developing countries, and steeply regressive across countries. Refunding revenues via national carbon dividends would reverse all three findings. The net effect would be globally progressive, even without international transfers. My approach to estimating the global distributional effects of carbon pricing uses bilateral trade data and features non-homothetic consumers who differ both between and within countries. The supply side includes substitution of inputs along global value chains.

JEL codes: F18, H23, Q56, Q58.
Keywords: Climate Policy, Environmental Tax, Redistributive Effects.

Financial disclosure: I gratefully acknowledge financial support from the UK's Economic and Social Research Council (ESRC) and the Grantham Research Institute on Climate Change and the Environment at the London School of Economics.

Conflict of interest: none.

---

*McCourt School of Public Policy & Department of Economics, Georgetown University, 37th and O Streets NW, Washington, DC 20057, USA. E-mail: lutz.sager@georgetown.edu. I thank Simon Dietz, Antony Millner, George Akerlof, Ian Bateman, Lucas Bretschger, Raphael Calel, Brian Copeland, Tom DeLeire, Swati Dhingra, Eugenie Dugoua, Nada Eissa, Robert Elliott, Marc Hafstead, Timo Hener, Michael Jakob, Ara Jo, Arik Levinson, Ralf Martin, John Morrow, Gianmarco Ottaviano, Henry Overman, Lindsay Relihan, Sefi Roth, Olmo Silva, Gonzague Vannoorenberghe, Felix Vetter, and Roberton Williams III for helpful comments. I also thank seminar participants at the ASSA 2021 Virtual Annual Meeting, the 3rd Joint IMF-OECD-World Bank Conference on Structural Reforms, the EAERE Annual Conference 2020, the NBER EEE Program Spring Meeting 2020, Georgetown University, LSE, UCLouvain, Aarhus University, ETH Zurich, University of Exeter, RFF, MCC Berlin, the AERE Summer Conference 2019, the 3rd CEPR/EBRD/LSE Economics of Transition Symposium, the EAERE Annual Conference 2019, the RES PhD Meeting 2018, the SAEe 2018, the RES Annual Conference 2019, and the 34th Annual Congress of the EEA.
Previous working paper version made available online here: *GRI Working Paper No. 320*, April 2019.

Abstract: Carbon pricing is often seen as regressive, disproportionately burdening low-income consumers. I show that higher prices following a global carbon price would be mildly regressive in industrialized countries, mildly progressive in developing countries, and steeply regressive across countries. Refunding revenues via national carbon dividends would reverse all three findings. The net effect would be globally progressive, even without international transfers. My approach to estimating the global distributional effects of carbon pricing uses bilateral trade data and features non-homothetic consumers who differ both between and within countries. The supply side includes substitution of inputs along global value chains.

1. Introduction

Governments around the world have begun pricing emissions of carbon dioxide (CO_2) and other greenhouse gases. In 2005, when the European Union (EU) launched its Emissions Trading System (ETS), less than 5% of global greenhouse gas emissions were subject to a price. In 2020, price coverage surpassed 15% and, with the newly launched permit scheme in China, now likely exceeds 20% (World Bank and Ecofys, 2020). A carbon price pushes consumers to buy less emissions-intensive goods and producers to use cleaner inputs. But it also has a cost, especially to consumers who may see prices rise. I ask how this cost is distributed globally.

Taking into account the propagation of carbon prices through global value chains, I estimate how the consumer cost of carbon pricing is distributed globally—both between countries and across income levels within them. Between countries, differences are shaped by the composition of aggregate consumption and the 'greenness' of production—consumers in countries that rely heavily on fossil fuel inputs face higher price increases. Within countries, consumption baskets vary with income and so do consumer costs. A global distributional analysis of carbon pricing needs to capture both of these margins. Ignoring either one would risk misrepresenting the welfare cost to large groups of consumers, since there are many high-income consumers even in the poorest countries and many low-income consumers in rich countries. Moreover, even consumers with similar incomes can face substantially different carbon pricing burdens based on where they live. By estimating a combined, global cost distribution, this paper contributes a new perspective to the analysis of carbon pricing.

To estimate the global consumer cost of carbon pricing, I calibrate a global model of demand and supply using a trade gravity approach. On the demand side, I estimate a global demand system using data on the final goods trade between 35 sectors and 40 countries in the World Input-Output Database (WIOD). I build on work by Fajgelbaum and Khandelwal (2016) who propose a global Almost Ideal Demand System (AIDS) which can be parameterized using gravity equations. The model includes non-homothetic preferences—expenditure shares vary with income—which are essential to capture distributional effects within countries. Fajgelbaum and Khandelwal (2016) use their model to estimate the distribution of the gains from trade. I use this non-homothetic gravity approach to analyze the global cost of carbon pricing.

On the supply side, I model substitution of intermediate inputs in global value chains, again using gravity equations to identify model parameters from inter-industry trade flows. A carbon price leads to shifts in global production as emissions-intensive inputs become more expensive. I also allow producers to substitute energy fuels. These supply side adjustments mediate the cost increase to consumers and render my estimates more realistic. A naive extrapolation ignoring supply side adjustments significantly over-estimates the consumer cost.

I assess three climate policy scenarios. The first is a global uniform carbon price, suggested by economic theory as an efficient response to the global climate externality. The global effects are highly regressive. Consumers in the bottom half of the world income distribution suffer an equivalent variation welfare loss more than twice as large as consumers in the top 10%. Importantly, differences between countries dominate those within them. Carbon pricing affects average consumers in poor countries more than poor consumers in average countries. I show that these differences between countries are mostly due to the emissions intensity of production rather than differences in the composition of aggregate consumption.

It has been shown that the distributional effect of national carbon prices ultimately depends on how revenues are used (Metcalf, 2009; Gonzalez, 2012) and I show that this also holds globally when simulating national per capita lump sum transfers. Such 'carbon dividends' feature in many carbon pricing proposals, including that by the Climate Leadership Council for the United States[1]. Carbon dividends render the global uniform carbon price progressive—disproportionately benefiting low-income consumers—both within countries and globally. This demonstrates that carbon pricing with appropriate revenue use can be globally progressive, even in absence of international transfers. And I show that the achieved mitigation benefits would likely be globally progressive as well.

A global uniform carbon price may not be likely anytime soon. I thus investigate two further scenarios that are more acutely policy relevant. For one, I simulate the introduction of the EU ETS in 2005. There is a growing literature studying the design and effectiveness of the EU ETS (surveyed in Ellerman and Buchner, 2007; Martin et al., 2016), but less is known about its distributional effects. I find that the EU ETS looks regressive across the 490 million European consumers, again driven by between-country differences: consumers in Eastern Europe and Baltic EU states are most affected. Finally, I investigate Border Carbon Adjustments (BCA) to counter competitive pressures and carbon leakage under unilateral climate policy (Markusen, 1975; Hoel, 1996). Recent plans for the 'European Green Deal' include proposals for a BCA-type mechanism[2]. I find that complementing an EU-wide carbon price with BCA would generate a rather small consumer cost, which is distributionally neutral.

My findings are subject to limitations. Mine is a partial equilibrium framework that focuses on 'use side' effects—the cost to consumers from higher prices. While the model allows for demand substitution, value chain adjustments and fuel shifting, it excludes other, potentially important effects of carbon pricing. In particular, it abstracts from shifts in factor markets that may affect incomes (Fullerton and Heutel, 2007; Rausch et al., 2011) and from energy-saving technological change (Acemoglu et al., 2012a; Aghion et al., 2016). The framework also imposes substantial

[1]The Climate Leadership Council's plan is available at https://www.clcouncil.org/.

[2]The EU's plan, including proposals for a Carbon Border Adjustment Mechanism (CBAM), is available at https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en.

structure. Perhaps the most important caveat is that, in absence of globally harmonized micro-data, I estimate demand system parameters from aggregate trade flows between countries. Because this relies on strong assumptions, I test my model against consumer survey data from multiple countries, finding a good fit. I also show that the main results are robust to alternative data sources and parameter choices.

This article contributes to the literature on the distributional effects of environmental policy (Drupp et al., 2021). Much of this literature is focused on the within-country effects of unilateral climate policy. Previous work suggests that the consumer cost of carbon pricing and related fuel taxes is somewhat regressive, at least in rich countries such as the United States (Poterba, 1991; Grainger and Kolstad, 2010; Williams et al., 2015). However, results vary with modeling choices and revenue use (West and Williams, 2004; Rausch et al., 2011). And results may differ across countries, with fuel taxes appearing regressive in some countries, but progressive in others (Sterner, 2012). A separate literature has focused on estimating how average effects differ between countries (early examples are Whalley and Wigle, 1991; Shah and Larsen, 1992), and how those differences shape climate policy negotiations (e.g. Mehling et al., 2018). This paper contributes estimates of the global consumer cost of carbon pricing accounting for differences both between and within countries. In line with single-country studies, I estimate that carbon pricing is moderately regressive in some, mostly rich countries and moderately progressive in poorer ones. But my results also highlight that differences between countries, driven mainly by value chain emissions, are more important in shaping how costs are distributed across the world income distribution. Finally, my results confirm that the progressivity of 'carbon dividends' holds at the global scale, even before between-country transfers.

2. Modeling the global cost of carbon pricing

I estimate how the consumer cost of carbon pricing is distributed globally—both between countries and at different income levels within them. To do so, I combine a global demand system with a model of global value chain adjustment and input-output based emissions accounting.

My model is not a complete general equilibrium model, but is intended to capture, while remaining tractable, those dynamics that I consider especially important in this context. On the demand side, consumers adjust their expenditures in response to rising final goods prices induced by carbon pricing. On the supply side, producers can substitute away from carbon-intensive energy fuels as they become more costly and away from dirty intermediate inputs. This shifts global value chains and mitigates price increases experienced by consumers. In this section, I present the model. In the next section, I estimate model parameters from bilateral trade flows. Appendix A provides further detail.

2.1. Demand: A global Almost Ideal Demand System

The core of my model is an Almost Ideal Demand System (AIDS) extended to multiple countries. Key to capturing distributional effects, AIDS incorporates non-homothetic preferences—consumers at different income levels within countries spend different shares of their income on emissions-intensive goods. Households $h = 1, \ldots H$ have total expenditure budgets x_h which they divide among goods $j = 1, \ldots J$ in a fashion summarized by expenditure shares:

$$s_j(\mathbf{p}, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{j'=1}^{J} \gamma_{jj'} \log\left(p_{j'}\right) + \beta_j \log\left(\frac{x_h}{a(\mathbf{p})}\right) \tag{1}$$

The share of expenditure that h devotes to good j (s_j) depends on preferences for good j (α_j), prices of all goods j' ($p_{j'}$) and h's real income ($\frac{x_h}{a(\mathbf{p})}$), normalized by price index $a(\mathbf{p})$ based on price vector $\mathbf{p}$. The degree of demand substitution is captured by cross-price elasticities between j and other goods j' ($\gamma_{jj'}$). Non-homothetic consumption is captured by the income (semi)-elasticity of j (β_j), which drives different expenditure shares across income groups. A positive value ($\beta_j > 0$) means that good j is a luxury and it is a necessity if $\beta_j < 0$.

While allowing for non-homothetic consumption, AIDS maintains convenient aggregation, a property that I use in Section 3 to estimate demand elasticities from the trade flow of final goods between countries. Here, I follow closely the methodology proposed by Fajgelbaum and Khandelwal (2016), who estimate how the gains from trade are distributed across consumers. The approach pairs AIDS with the assumption of national product differentiation (Armington, 1969). Each sector $s = 1,..S$ from each country of origin $i = 1,...I$ produces a different variety, so that the total number of goods is $J = S \times I$. Destination countries are labeled $n = 1,...N$. Consumers' average tastes differ by destination (α_{nj}), but consumers in all countries share the same price and income elasticities ($\gamma_{jj'}$ and β_j). These are strong assumptions, which I test against country-level consumer survey data in Section 5.

I quantify welfare effects as Hicksian equivalent variation—the share of income that a consumer would give up for a price increase not to occur:

Proposition 1 (Welfare Effect) *The marginal welfare effect of a small change in (log) prices of goods j, $\{\hat{p}_j = dlog(p_j)\}$, experienced by consumer h in country n is:*

$$\begin{aligned} \hat{\omega}_{nh} &= \sum_{j=1}^{J} (-\hat{p}_j)\, S_{nj} \quad - \left(\sum_{j=1}^{J} \beta_j \hat{p}_j\right) \log\left(\frac{x_{nh}}{\tilde{x}_n}\right) \quad + \hat{x}_{nh} \\ &= \hat{W}_n \qquad\qquad\quad + \hat{\psi}_{nh} \qquad\qquad\qquad\qquad + 0 \end{aligned} \tag{2}$$

Proof. See Appendix A.1, following Fajgelbaum and Khandelwal (2016). ■

The welfare cost from higher prices can be separated into an aggregate cost common to all consumers in country n ($\hat{W}_n$) and an individual cost to each consumer h ($\hat{\psi}_{nh}$). The former is a function of the aggregate expenditure share on good j by consumers in country n (S_{nj}). The latter is a function of h's income (x_{nh}) relative to the inequality-adjusted mean income ($\tilde{x}_n$) in the country[3], shaping the deviation from average expenditure patterns as driven by income elasticities β_j. In other words, $\hat{W}_n$ captures the average consumer incidence between countries while $\hat{\psi}_{nh}$ captures distributional effects within countries[4]. The final element is the change in h's (log) nominal income $\hat{x}_{nh}$, which I generally assume to be unaffected by carbon pricing ($\hat{x}_{nh} = 0$), except when

[3] Inequality-adjusted real income is $\tilde{x}_n = \bar{x}_n e^{\Sigma_n}$ where $\Sigma_n = \mathrm{E}\left[\frac{x_{nh}}{\bar{x}_n} \log\left(\frac{x_{nh}}{\bar{x}_n}\right)\right]$ is the Theil index of inequality.

[4] In simulations with non-marginal changes in prices $\hat{\mathbf{p}}$, equation (2) is integrated numerically to account for demand substitution in 5 intermediate steps between initial and new prices.

investigating a carbon dividend policy.

2.2. Supply: Input substitution in global value chains

Producers react to changes in input costs by moving away from emissions-intensive inputs. This in turn reduces the amount of emissions embodied in final goods and softens the price increase to consumers. To capture such supply-side adjustments, my model tracks emissions throughout global value chains and allows for intermediate input substitution.

For simplicity I assume that production requires only energy and a composite of intermediates, in fixed proportions. Producers in each country-sector j, all assumed to be perfectly competitive, have identical Constant Elasticity of Substitution (CES) production functions across intermediate inputs $k = 1, ...K$ with destination-specific prices ρ_{kj}. All country-sectors produce intermediates and final goods, so that $J = K$. For any level of output X_j in country-sector j, the representative producer minimizes input costs C_j, resulting in the following cost shares spent on intermediates k:

$$E_{kj} = \frac{\rho_{kj} f_{kj}}{C_j} = \theta_{kj} \rho_{kj}^{(1-\sigma_j)} P_j^{(\sigma_j - 1)} \tag{3}$$

The cost share of input k, E_{kj}, depends on a technology factor θ_{kj}, which defines the cost share under equal input prices. E_{kj} is decreasing in the price of k, ρ_{kj}, relative to the input price index $P_j = (\sum_k \theta_{kj} \rho_{kj}^{(1-\sigma_j)})^{1/(1-\sigma_j)}$. With constant returns to scale and perfect competition, input shares and output prices are independent of the level of final demand. Prices remain proportional to input cost at all times.

In Section 3, I estimate substitution elasticities σ_j, this time using data on inter-industry trade flows of intermediates. Once parameterized, I simulate input substitution in response to carbon pricing and approximate the new equilibrium in global input-output linkages. To trace emissions, and their price effect, through value chains, I use input-output based accounting methods which capture all indirect emissions embodied in consumption (e.g. Levinson and O'Brien, 2019; Sager, 2019). Value chains are summarized by the Direct Requirement matrix $\mathbf{A}$ with elements a_{kj} which show the dollar amount of intermediate input from country-sector k used to produce a dollar of output in country-sector j. Following Leontief (1970), the relationship between the J-vectors of final goods output $\mathbf{y}$ and total output including intermediates $\mathbf{x}$ is as follows:

$$\mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{y} = \mathbf{T}\mathbf{y} \tag{4}$$

This yields the Total Requirement matrix $\mathbf{T} = [\mathbf{I} - \mathbf{A}]^{-1}$ with elements t_{kj} showing the dollar amount of total input from country-sector k used to produce a dollar of final output in country-sector j, accounting for all upstream processes. The same accounting applies to emissions:

$$\mathbf{e} = \mathbf{T}'\mathbf{d} \tag{5}$$

The J-vector $\mathbf{d}$ of direct emissions intensities d_j describes for each country-sector j the CO_2 emissions per dollar of output (tons of CO_2 per \$). Taking into account upstream emissions, elements e_j of vector $\mathbf{e}$ show the total CO_2 intensity of a dollar of final consumption generated by country-sector j, including all upstream emissions. The total emission intensity e_j of final goods produced by country-sector j determines its relative price increase[5].

Price dynamics:

Assume a carbon price τ (in \$ per ton of CO_2) is put on all emissions. In a static model, this raises final prices to $p_j^* = (1 + \tau e_j)p_j$. When allowing for intermediate input substitution, adjustments will alter value chains ($\mathbf{A}$) and, consequently, emissions intensities (e_j). This will invite yet further adjustments to inputs until we reach a new equilibrium:

Proposition 2 (Price effect with input substitution) *Assume a set of carbon prices $\{\tau_{kj}\}$ is levied on intermediates k used in production j. Given initial input requirements $\{a_{kj}\}$ and di-*

[5]Price increases of final goods are the same whether carbon prices are levied at the source in the form of taxes on fossil fuels or in the form of a consumption tax levied on the CO_2 content of final goods. Due to perfect competition, producers will fully pass-through price increases to consumers and competitive firms will internalize carbon prices even if they were collected at the point of sale. The distinction between consumption and production taxes can affect the country where revenue is collected, however.

rect emissions intensities $\mathbf{d}$*, the new equilibrium is defined jointly by:*

$$a^*_{kj} = a_{kj} \left(\frac{\sum_{k'=1}^{K} \theta_{k'j} (1+\tau_{k'j} e^*_{k'})^{(1-\sigma_j)})^{1/(1-\sigma_j)}}{1+\tau_{kj} e^*_k} \right)^{\sigma_j} \quad \forall k, j \tag{6}$$

$$\mathbf{e}^* = \left[(\mathbf{I} - \mathbf{A}^*)^{-1} \right]' \mathbf{d} \tag{7}$$

Proof. See Appendix A.2. ■

For each carbon pricing scenario, I approximate numerically the new equilibrium value chain ($\mathbf{A}^*$), emission intensities (e^*_j) and prices (p^*_j). The procedure is described in Appendix A.3.

Fuel switching:

Besides intermediate input substitution, I model fuel switching in production between 4 primary fuel groups: Coal, Gas, Oil, and Renewables[6]. The key assumption is that the total amount of energy content (in TJ) needed to produce one unit of output in each sector is constant, but that producers can shift between the fuels to generate that energy[7]. Here, I rely on meta-survey estimates of pairwise interfuel substitution by Stern (2012)[8], paired with data on CO_2 emission intensities that vary by country-sector and fuel type. In the data I use, described in Section 3, emissions are assigned to that sector where the fuel is combusted (Genty et al., 2012), rather than to the mining and petroleum sector supplying it. Fuel switching thus generates new direct emission intensities d^*_j, which then feed into the intermediate input substitution process that results in $\mathbf{A}^*$ and e^*_j. The most quantitatively important fuel switching occurs in the electricity sector, where coal tends to be replaced with gas and renewables when carbon is priced. The reduced direct emission intensity (d^*_j) of the electricity sector in turn lowers the total emissions of all downstream sectors (e^*_j).

Discussion and Limitations:

[6] I group WIOD energy-related emissions as follows: Coal (anthracite, lignite and coke); Oil (gasoline, Diesel, jet kerosene, LFO, HFO and naphtha); Gas (natural and other gas); Renewables (biogas, bio diesel, electricity, heat production, nuclear, hydropower, geothermal, solar, wind).

[7] Fuel substitution uses annual average fuel prices from the BP Statistical Review of World Energy and emissions content from the IEA 2006 Guidelines on Default Carbon Content Values.

[8] Results are similar when I assume that energy services are produced in a CES production function over fuel inputs with the same parameters as for intermediates in (3).

The primary purpose of my model is to capture distributional effects across consumers in many countries and at different income levels. I focus on the "use-side" effects—the cost to consumers from higher final goods prices, accounting for demand substitution. The adjustments on the supply side—fuel switching and intermediate input substitution—mitigate the price increase passed on to consumers and render the incidence estimates more realistic.

My model excludes other margins of adjustment that may be important. I assume perfect competition and constant returns to scale, which means that input prices, other than the carbon price element, remain fixed. There is no adjustment in the price of production factors such as capital or labor, and carbon prices are fully passed through to consumers. Equilibrium price adjustments would likely mitigate the cost increase experienced by consumers, though supplier market power may partially offset that. And imperfect pass-through of prices to consumers, for which there is evidence in some industries (Ganapati et al., 2019), would similarly mitigate consumer welfare losses.

While I allow for fuel switching, including replacement of fossil fuels with renewable energy sources, my model is static in the sense that it assumes a constant share of energy in production. This precludes the possibility that energy inputs are partially substituted with other inputs such as natural resources or labor. I also assume a constant degree of substitutability between fuels, excluding the possibility that carbon pricing induces energy-saving innovation in production technologies (Aghion et al., 2016). While I allow for differential effects of carbon pricing by sector and country of origin, my framework holds other factors influencing global trade patterns constant. In particular, I ignore induced fluctuations in exchange rates, which may be substantial under border tax adjustments (Barbiero et al., 2019). Again, it seems likely that exchange rate adjustments would soften the induced price differentials between countries and thus lower consumer burdens. I also hold transport margins fixed, even though transport costs themselves may be affected by carbon prices (Shapiro, 2016).

Finally, while I will highlight additional channels such as the use of carbon pricing revenues for transfers and the distribution of mitigation benefits, I ignore other welfare-relevant effects that may occur via labor markets or shifting factor incomes (Rausch et al., 2011).

3. Calibrating the model

My model is calibrated using Multi-Regional Input-Output (MRIO) databases that capture flows of intermediate and final goods between country-sector pairs. I mainly use the World Input-Output Database (WIOD) Release 2013, which covers 35 sectors in 40 countries (plus 'Rest of the World'), between 1996 and 2009. WIOD contains bilateral trade flows between country-sector pairs and input-output relationships ($\mathbf{A}$). WIOD environmental satellite accounts document CO_2 emissions by fuel type for each country-sector (d_j). Appendix Table 5 provides an overview of the consumption and emissions profiles of the 40 countries.

While WIOD is one of the most commonly used MRIO databases[9], I show that my results carry through with a different data source, the harmonized version of Eora (Eora 26), which covers 189 countries and 26 sectors, as recently as 2015. This section summarizes how I estimate the remaining model parameters from bilateral trade flows, with further details provided in Appendix B.

3.1. Demand: Estimating demand system parameters

To identify demand elasticities, I follow Fajgelbaum and Khandelwal (2016) in embedding AIDS demand in a multi-sector Armington model of international trade so that each sector $s = 1,..S$ from each country of origin $i = 1,...I$ sells a different variety of final goods. Consumers in destination countries $n = 1,...N$ choose from these varieties, of which there are 1400 in WIOD ($J = S \times I = 35 \times 40$).

Trade costs between country-pairs (t_{ni}) are of the iceberg variety[10], adding a constant multiple

[9] One limitation of using WIOD data is that it cover only 35 sectors of the economy. It cannot capture substitution of intermediate goods within sectors as more fine-grained analyses might (as e.g. Levinson, 2009, who distinguishes 450 manufacturing industries in the US). However, WIOD is one of the few sources for harmonized MRIO accounts and substitution between the 35 sectors should already capture a significant portion of input substitution.

[10] This proportionality of trade costs is maintained in counterfactual analyses under carbon pricing

to prices $p^s_{ni} = t_{ni} p^s_i$. I estimate income semi-elasticities (β^s_i) for each of the 1400 varieties and price elasticities (γ^s) for the 35 sectors, assuming that substitution is symmetric and restricted to goods in the same sector from different origins. The estimation strategy follows closely that by Fajgelbaum and Khandelwal (2016) and produces very similar estimates. A detailed description is given in Appendix B.1. I estimate the following equation for aggregate expenditure shares (S^s_{ni}) by consumers in country n on goods from sector s and country i:

$$S^s_{ni} = \frac{Y^s_i}{Y_W} + \alpha_i (S^s_n - S^s_W) - (\gamma^s \rho^s) D_{ni} + \sum_l (\gamma^s d^s_l) G_{l,ni} + (\beta^s_i - \alpha_i \overline{\beta}^s) \Omega_n + \varepsilon^s_{ni} \tag{8}$$

Consumers in destination n buy more from sector s in origin i if that sector accounts for a larger share of world total output ($\frac{Y^s_i}{Y_W}$) and if consumers in n spend more on goods from sector s relative to the world ($S^s_n - S^s_W$). Variation in bilateral trade costs (D_{ni}), which apply proportionately to sector-level costs (ρ^s), helps identify within-sector price elasticities (γ^s). If trade is more concentrated among less distant country pairs within one sector than another, I estimate that the former sector faces more price-elastic demand. As proxy for bilateral trade cost, I use data from CEPII's Gravity database on the population-weighted log-distance between country pairs (D_{ni}), as well as binary indicators for common language and a shared border ($G_{l,ni}$).

Variation in the inequality-adjusted mean real income[11] of destination n relative to the world ($\Omega_n = y_n - \overline{y}_W$) identifies income elasticities (β^s_i). If textiles from the United States are consumed more in richer and more unequal countries than textiles from India, then American textiles have a higher income elasticity. Ω_n is based on country population and GDP per capita from the Penn World Tables and, assuming that income is log-normally distributed, the Gini index of income inequality from the World Income Inequality Database (WIID). Following the methodology of Fajgelbaum and Khandelwal (2016), I also proxy for the non-homothetic price index $a(\mathbf{p})$ with a Stone price index for each destination country n using quality-adjusted prices as provided by Feenstra and Romalis (2014). To pin down $\hat{\gamma}^s$, I follow Novy (2013) in setting $\rho^s = \rho = 0.177$

[11] Inequality-adjusted mean real income is $y = \log\left(\frac{\tilde{x}}{a(\mathbf{p})}\right)$ where $\tilde{x} = \overline{x} e^{\Sigma}$ and $\Sigma = \mathrm{E}\left[\frac{x_h}{\overline{x}} \log\left(\frac{x_h}{\overline{x}}\right)\right]$.

for all s. To estimate sector-average income elasticities $\overline{\beta}^s$, I estimate a second Engel curve for country-level aggregate expenditure shares:

$$S_n^s = \alpha^s + \overline{\beta}^s y_n + \varepsilon_n^s \tag{9}$$

Estimates of $\overline{\beta}^s$ together with estimates of α_i from the above gravity estimation identify origin-sector specific income semi-elasticities β_i^s.

3.2. Supply: Estimating production function parameters

On the supply side, I estimate intermediate substitution elasticities using data on bilateral inter-industry trade. I consider intermediate flows between destination sector s in country n (labeled j above) and origin sector s' in country i (labeled k above). In WIOD there are 1.96m ($= 1400^2$) such country-sector pairs.

I again assume that each sector s' in origin i produces a distinct input variety ($K = S \times I$) and that the market for intermediate goods is perfectly competitive. I further assume that prices are the same for intermediates and final goods from each sector s ($\rho_{ni}^s = p_{ni}^s$) and that both are subject to iceberg trade costs t_{ni} between destination n and origin i ($p_{ni}^{s'} = t_{ni} p_i^{s'}$). Finally, I assume that production functions are identical in sectors s across countries n ($\sigma_{n,s} = \sigma_s$ and $\theta_{ni}^{ss'} = \theta_i^{ss'}$, $\forall n$).

I estimate the following equation for the cost share in sector s and destination n that goes to intermediates from sector s' in origin i, denoted $E_{ni}^{ss'}$:

$$\log\left(E_{ni}^{ss'}\right) = (1-\sigma_s)\rho \log\left(D_{ni}\right) + \sum_l \left[(1-\sigma_s) d_l \log\left(G_{l,ni}\right)\right] + \lambda_n^s + \zeta_i^{s'} + \varepsilon_{ni}^{ss'} \tag{10}$$

Sector-specific CES production elasticities σ_s are identified from cross-sectional variation in bilateral trade costs, which are again proxied by bilateral distance between country pairs (D_{ni}) from CEPII. The other elements of $G_{l,ni}$ are indicators for common language and a shared border, also from CEPII. λ_n^s and $\zeta_i^{s'}$ are fixed effects for destination and origin country-sectors respectively.[12]

[12] For estimation, run ordinary least squares (OLS) with origin/destination country-sector fixed effects, which has been

This is similar to standard CES gravity estimation following Anderson (1979) and Anderson and Van Wincoop (2003), with details provided in Appendix B.2. I estimate this equation separately for the 35 sectors s and restrict substitution to inputs from the same sector across different origins. American electronics producers can substitute Swedish metal for Chinese metal, but not for textiles.[13]

3.3. Model overview and parameter estimates

While previous studies have used trade gravity approaches to inform climate policy (Shapiro, 2016; Larch and Wanner, 2017; Caron and Fally, 2018), I focus more narrowly on distributional effects. Table 1 summarizes the key components of my model used to estimate welfare effects of global carbon pricing scenarios across consumers in different countries and at different income levels within them. The global AIDS framework allows for non-homothetic preferences via origin-sector specific income semi-elasticities (β_i^s), as well as consumer substitution across origins within sectors via price elasticity parameters (γ^s). Both income and price elasticities of demand are estimated from equations (8) and (9) using WIOD (or Eora) data on bilateral final goods trade following Fajgelbaum and Khandelwal (2016). In the case of WIOD, there are 1400 country-sector specific income (β_i^s) and 35 sector-specific price elasticity (γ^s) parameters.

The supply side model allows for substitution of intermediate inputs across origins within sector via CES elasticities (σ_s). These are estimated from equation (10) using inter-industry trade flows. Substitution across primary energy fuels—coal, oil, gas and renewables—is based on the assumption of constant energy need (in TJ) per output paired with interfuel substitution elasticities from a literature survey (Stern, 2012).

Parameter robustness: I provide a summary of parameter estimates in Appendix D. Since they are based on cross-sectional patterns of bilateral trade flows, it is plausible to assume that they

shown to be consistent (e.g. Head and Mayer, 2014). I again assume that $\rho = 0.177$.

[13]Simulations show that allowing full substitution across input sectors further softens price increases, but does not overturn any of the qualitative findings reported below.

Table 1: Method overview

	Theory	Parameters	Data
Demand	AIDS preferences (by country-sector)	Income elast. (β_i^s) Price elast. (γ^s) (estimated)	Final goods trade (WIOD, Eora)
Supply: Input substitution	CES production (by sector)	CES elast. (σ_s) (estimated)	Inter-industry trade (WIOD, Eora)
Supply: Fuel switching	Constant TJ per unit (by country-sector)	Interfuel elast. (Stern, 2012)	Fuel shares (WIOD, Eora)

Notes: Overview of the key model characteristics and data sources.

represent long-term elasticities. The CES elasticity estimates are relatively large, averaging around $\sigma_s \approx 4$. While this is similar in magnitude to the long-run elasticity estimates for intermediate substitution by Peter and Ruane (2018), excessive substitution may result in an underestimate of price increases experienced by consumers. The same could be said of the degree of interfuel substitution. I show in sensitivity analyses that excluding either form of substitution generates larger absolute costs, but with a very similar distribution.

My demand elasticities are nearly identical to those of Fajgelbaum and Khandelwal (2016) who also provide an extensive discussion of the limitations to this approach. Reassuringly, the estimates are highly consistent over time and appear plausible. For example, agricultural output is consistently classified as a necessity ($\hat{\beta}_s < 0$) and real estate services as a luxury good ($\hat{\beta}_s > 0$). Within sectors, varieties from the United States and Japan appear more likely to be luxury goods, while varieties from India and Indonesia are necessities. As discussed above, I rely on the assumption that we can interpolate consumption at different income levels from differences in aggregate demand between countries. To test this admittedly strong assumption, I compare my results to consumer survey data from multiple countries, finding a relatively good fit.

I perform further sensitivity analysis in two ways. First, I include confidence intervals from simulations using random parameter draws ($\hat{\beta}_i^s$, $\hat{\gamma}^s$) from the joint normal distribution implied by regression estimates. Second, I compare results using two different data sources, WIOD and Eora, which yield two separate sets of parameter estimates, but similar results.

4. The global consumer cost of carbon pricing

I estimate the global consumer cost under three carbon pricing scenarios. First, I simulate a global carbon price uniformly applied in all countries. This is what economic theory may suggest as an efficient response to the global climate externality. I use 2004 as a baseline year, as it is before the introduction of the first large-scale carbon pricing scheme, the EU Emissions Trading System (ETS), though results look similar for later years. While a global uniform carbon price may not be realistic anytime soon, an EU-wide carbon price already exists. My second scenario is a stylized version of the EU ETS launched on January 1, 2005. Third, I simulate a policy of complementing an EU-wide carbon price with Border Carbon Adjustments (BCA) that target emissions in traded goods.

4.1. Scenario 1: A global uniform carbon price

I estimate the consumer cost from a global uniform carbon price of 30 USD per ton of CO_2 emissions from fossil fuel combustion[14]. Figure 1 shows how the resulting consumer cost is distributed across the global income distribution. The horizontal axis represents percentiles of the income distribution of the ca. 4.2 Billion residents living in the 40 WIOD countries in 2004. The vertical axis shows the average change in consumer welfare, expressed as a share of annual expenditure. The dashed line shows central estimates and the solid line a 10th degree polynomial approximation. The blue band represents 95% confidence intervals[15]. Negative values represent welfare losses.

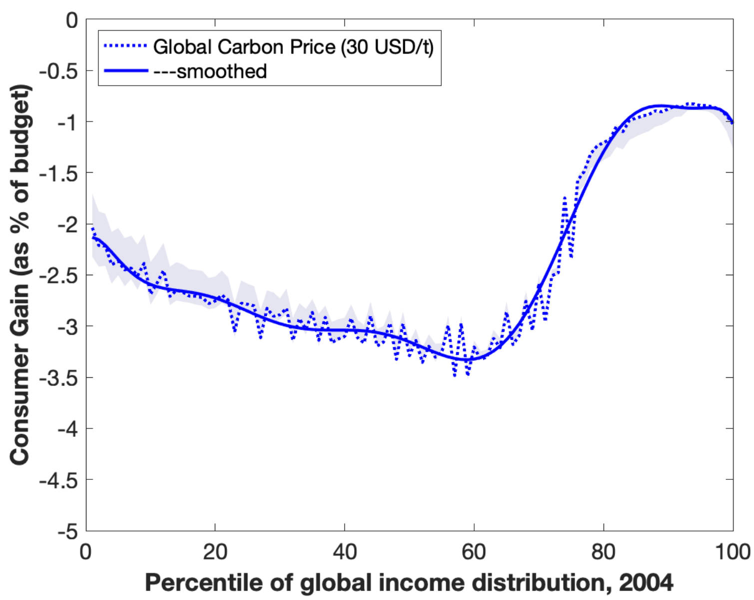
The first insight here is that a global carbon price is rather regressive at a global scale. The cost to consumers in the bottom half of the world income distribution—equivalent to losing between 2% and 3% of income—is more than twice as large as that of consumers in the top 20%. Because the pattern visible in Figure 1 is not monotonic, I confirm this regressivity more formally in Row (1) of Table 2, reporting average effects for quintiles of the global income distribution, along with

[14]Some may deem a carbon price of 30 USD per ton too low. I show in Appendix F that, while the overall cost is higher, the relative distribution is similar under a carbon price of 100 USD per ton.

[15]Confidence intervals are from 500 separate simulations, each using a different set of model parameters drawn from the joint normal distributions from estimations (8), (9) and (10).

two measures of progressivity. The first measure ('Linear') is the expected change in welfare effect when moving from one quintile to the next higher quintile, as predicted from a linear regression. Positive numbers indicate a regressive effect, as is the case here: Moving down by one quintile in the income distribution is associated with an increase in cost (a reduction in welfare) by 0.66 percentage points. The second measure ('Suits') is the measure of tax progressivity proposed by Suits (1977). This measure ranges from -1 to 1 and negative values suggest regressivity, as for this scenario with a Suits index of -0.18. The consumer cost of carbon pricing appears globally regressive.

Figure 1: Global price of 30 USD per ton - Global distribution of consumer cost



Notes: This figure shows the global distribution of the consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004 (40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 4.2 billion inhabitants of the 40 WIOD countries in 2004. The consumer gain is the average welfare effect, expressed as equivalent share of the total expenditure budget (dashed) and approximated with a 10th degree polynomial (solid). Shaded regions are 95% confidence intervals from 500 separate simulations, each using a different set of parameters drawn from the joint normal distributions from estimations (8), (9) and (10).

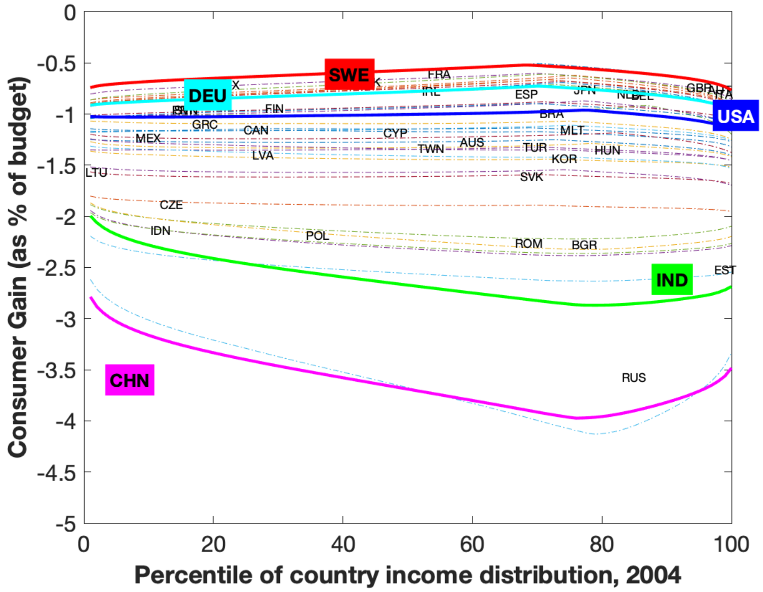
The second insight is that the burden varies drastically between countries. Figure 2 shows the cost distribution in each of the 40 countries, across percentiles of the country income distribution. These are simulated from equation (2) and thus smooth. Upward-sloping lines suggest that carbon pricing is regressive—with larger losses (negative values) to low-income consumers—and vice versa. In rich nations, such as Germany, Sweden and the United States, carbon pricing looks regressive. In developing nations, such as China and Indonesia, it looks somewhat progressive. This is in line with single-country studies, which find weak to moderate regressivity in rich (Poterba, 1991; Grainger and Kolstad, 2010) and progressivity in poor ones (Datta, 2010; Sterner, 2012; Dorband et al., 2019). It is also in line with recent simulation results from Chepeliev et al. (2021), who find significant between-region heterogeneity in the distributional effects of carbon pricing policies.

But Figure 2 also suggests a third, more nuanced insight: The consumer cost of carbon pricing varies much more strongly between countries than within them. For example, there is a mild difference in cost between American consumers at the 10th percentile of the income distribution (equal to 1.1% of expenditures) and those at the 90th percentile (1.0%). But there is a much greater difference with Chinese consumers, at either the 10th (3.3%) or 90th (4.0%) percentiles. Put differently, the slopes of the lines in Figure 2 are much less important than the distances between them. Differences between countries matter more than those within them.

'Greenness' of industry explains most of the between-country incidence:

The differences between countries shown in Figure 2 could be driven by differences in consumption baskets (Caron and Fally, 2018) or by differences in the emissions intensity of value chains (Copeland and Taylor, 1994; Levinson, 2009). It has long been recognized that national economic structure has important repercussions for environmental policy (Whalley and Wigle, 1991; Shah and Larsen, 1992). My estimates suggest that the 'greenness' of value chains is the more important factor to explain the consumer cost difference between countries. The reason is home bias: Chinese consumers spend much more of their budget on Chinese rather than, say, Swedish goods. The reverse is true for Swedes. Since value chains in China are more CO_2-intensive than those in Sweden, carbon pricing hurts Chinese consumers more than Swedish ones. To show that, I replicate the scenario discussed above, but equating the direct emissions intensities across all countries (d_j) to that

Figure 2: Global price of 30 USD per ton - Within-country consumer cost



Notes: This figure shows the distribution of the consumer welfare effect in each country under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004 (40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution within each of the 40 WIOD countries in 2004. The consumer gain is the average welfare effect, expressed as equivalent share of the total expenditure budget.

of the corresponding sector in Sweden. Even maintaining other differences between countries—in value chains and aggregate consumption baskets—this significantly reduces the global regressivity and nearly eliminates differences between countries. As shown row (2) of Table 2, the Suits index moves from -0.18 to -0.09, a marked decline in regressivity. The full visual replication can be found in Appendix Figure 7. Most of the higher cost of carbon pricing in lower income countries stems not from differences in consumption, but from more carbon-intensive modes of production.

National 'carbon dividends' result in global progressivity:

We have so far focused on the cost to consumers from higher prices that follow the introduction of carbon pricing policies. But carbon pricing may also generate revenues, which governments can use to offset that cost. It has been shown that the distributional effect of national carbon prices ultimately depends on how that revenues are used (Metcalf, 2009; Gonzalez, 2012). I confirm that this holds in my global analysis as well: the regressive cost of higher prices can be transformed into

Table 2: Scenario comparison - All prices of 30 USD per ton

	Welfare Effect (as % of budget)						Pro-/regressive (p/r)	
	Q1	Q2	Q3	Q4	Q5	Total	Linear	Suits
(1) Scenario 1: Global Price	**-2.59**	**-2.96**	**-3.19**	**-2.05**	**-0.92**	**-1.16**	**0.66** (r)	**-0.18** (r)
(2) Swedish emissions	-0.60	-0.68	-0.74	-0.55	-0.36	-0.4	0.14 (r)	-0.09 (r)
(3) Net of dividend	5.24	2.24	0.28	0.01	-0.19	-0.07	-1.09 (p)	
(4) Mitigation benefits	17.35	11.08	6.92	1.66	0.32	0.99	-3.86 (p)	
(5) Scenario 2: EU ETS	**-1.02**	**-0.49**	**-0.37**	**-0.32**	**-0.31**	**-0.37**	**0.19** (r)	**-0.13** (r)
(6) Scenario 3: EU BCA	**-0.42**	**-0.38**	**-0.32**	**-0.25**	**-0.31**	**-0.31**	**0.09** (r)	**-0.01** (r)

Notes: Overview of simulation results. Columns (1)-(5) show average consumer cost (as % of total budget) by quintile, and column (6) shows the total average. Column (7) shows the percentage point expected change in cost when moving from a given quintile to the next higher quintile, derived as the coefficient from a linear regression of consumer cost on percentile rank multiplied by 20. Negative values denote progressivity. Column (8) shows the measure of tax progressivity proposed in Suits (1977), with positive values denoting progressivity.

a globally progressive net effect with revenue recycling. This is shown in Figure 3. It assumes that governments redistribute 100% of the revenue collected by carbon pricing in their own country, sharing it in equal per capita fashion among all residents. Such 'carbon dividends' feature in many policy proposals, including that by the Climate Leadership Council for the United States.

Figure 3b shows that the net welfare effect of a global 30 USD per ton carbon price paired with carbon dividends would be progressive within all countries[16]. Lower income consumers may experience a larger loss in relative spending power, expressed as share of their budget (Figure 1). But they experience a smaller loss in absolute dollar terms. As a result, the equal lump sum payment is more than enough to compensate them. Meanwhile, the drop in spending power experienced by higher income consumers may be smaller relative to their budgets, but it is larger in absolute terms and not fully compensated by the dividend. Figure 3 further suggests that the net progressivity of carbon pricing with dividends is more pronounced in more unequal countries, which have a larger difference between low-income consumers and the average consumer who pays for the carbon dividend. In any case, the median consumer is better off after dividends in all 40 WIOD countries. It is important to clarify that the aggregate welfare effect remains negative once the relative effects

[16]Because some countries are net exporters/importers of emissions, it now matters where pricing occurs. Figure 3 assumes that revenue is collected and redistributed in the country where final consumption occurs. Appendix Figure 8 shows that a similar pattern holds when we tax in the country where emissions occur in production.

in Figure 3 are weighted by income, at least before we consider the benefits of avoided climate damage discussed below.

The progressivity of carbon dividends within countries may be unsurprising, but Figure 3a shows that the welfare effect is also globally progressive. Row (3) of Table 2 shows that the progressivity is substantial: The bottom three quintiles of the global income distribution are significantly better off with the policy, while the fourth quintile is largely unaffected and only the highest quintile experiences a net welfare loss. Overall, 70% of consumers worldwide are better off with carbon pricing plus dividends. It is important to note that this scenario does not include any transfers between countries. Each country recycles only those revenues raised domestically. The progressivity within each country appears to outweigh any average differences in welfare cost between countries. One possible factor contributing to this may be the higher levels of income inequality in low-income countries, which results in an even larger progressivity as seen in Figure 3b. National carbon prices plus dividends are sufficient to achieve a globally progressive climate policy.

Consumer cost is likely complemented by progressive mitigation benefits:

In addition to price changes and income transfers from carbon dividends, carbon pricing may result in other welfare-relevant changes. One important aspect are the benefits from reduced greenhouse gas emissions, which are likely to be substantial and unevenly distributed. Climate damages, and hence the benefits from reducing them, will likely fall disproportionately on places that are already hot today, that lack adaptive capacity and that rely heavily on vulnerable activities such as agriculture and manual labor (Dell et al., 2012; Burke et al., 2015; Ricke et al., 2018). All of which tend to be correlated with lower income levels.

I use estimates from elsewhere in the literature to compare the consumer cost estimated here to the likely benefits from emissions reductions. Row (4) of Table 2 shows estimates of the mitigation benefits achieved by the global carbon price of 30 USD per ton simulated here. Reductions in CO_2 emissions are valued using the country-level Social Cost of Carbon (SCC) estimated by Ricke et al. (2018) and converted into relative income shares[17]. The mitigation benefits are highly progressive.

[17] I use the central estimates from the "Middle of the road" scenarios in Ricke et al. (2018), specifically

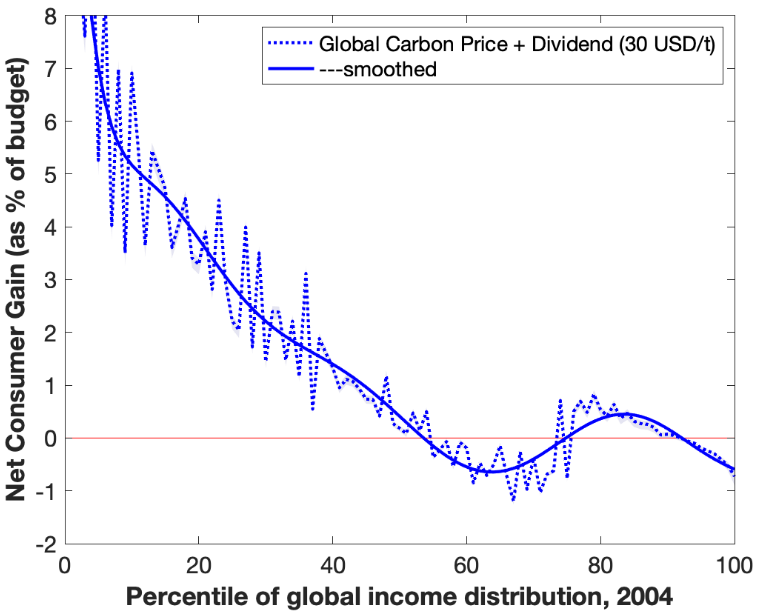
Even without revenue recycling, the combined effect, the sum of rows (1) and (4), would likely be positive for the 3 bottom quintiles of the world income distribution. When revenue is recycled through a carbon dividend, all quintiles are likely to gain and especially those with lower incomes.

Other dynamics with potentially important distributional consequences are less easily captured. For example, carbon pricing is likely to induce shifts in factor incomes. Estimates for individual rich countries suggest that these 'source-side' effects may be progressive (Goulder et al., 2019), in part by raising the share of income flowing to workers relative to owners of capital (Fullerton and Heutel, 2007; Rausch et al., 2011). It is plausible that a similar shift would occur in lower income countries, again leading to a progressive effect. The framework used here does not capture the relevant general equilibrium effects and thus cannot quantify these 'source-side' effects. However, recent simulation results from Chepeliev et al. (2021) suggest that carbon pricing may lead to lower skill wage premia, thus lowering global income inequality. Furthermore, we may expect dynamic adjustment processes, such as technological innovation spurred by carbon pricing (Acemoglu et al., 2012a; Aghion et al., 2016), and possibly important repercussions of market imperfections, such as search frictions in labor markets (Hafstead et al., 2022). Understanding their implications for the global burden of carbon pricing is a promising area for future research.

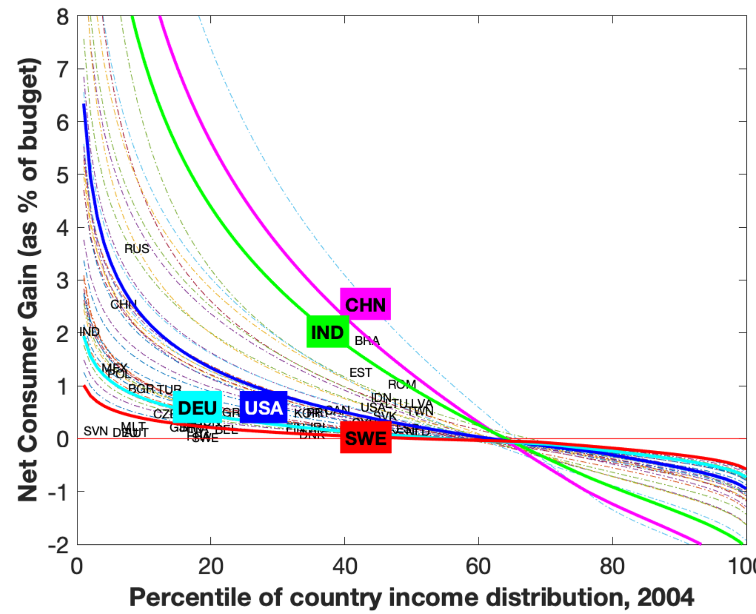
RCP6.0/SSP2/BHM-SR with a pure rate of time preference of 2% and an elasticity of marginal utility of 1.5%, converted to 2004 dollars. The combined SCC in this sample is $152.

Figure 3: Global price of 30 USD per ton and national carbon dividend - Consumer cost

(a) Global distribution



(b) Within-country distribution



Notes: Consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries), net of the benefits from a per capita carbon dividend in each country. Revenue is collected and redistributed in the country where final consumption occurs. The horizontal axis shows percentiles of the income/expenditure distribution, both globally (Panel a) and within each of the 40 WIOD countries (Panel b) in 2004. Otherwise equivalent to Figure 1 (Panel a) and Figure 2 (Panel b).

4.2. Scenario 2: The EU Emissions Trading System (ETS)

The European Union Emissions Trading System (EU ETS) launched on January 1, 2005. I estimate the consumer cost of a stylized EU ETS by calibrating my model to 2004 and simulating a price of 30 USD per ton levied on EU ETS target sectors[18] in 27 EU ETS countries[19].

Figure 4a shows that the consumer cost appears regressive across the 490 million EU residents. The bottom 10% of the EU income distribution incurs a cost equivalent to losing 1-1.5% of expenditure. For the top half of the distribution, that cost is below 0.5%. Regressivity is again confirmed by a negative Suits index, shown row (5) of Table 2. Just like before, Figure 4b shows only modest variation within countries, but larger differences between them. Consumers in EU member states with lower incomes, particularly Eastern European and Baltic states, experience a much higher cost than their peers in Germany or Sweden, no matter their incomes. This is again caused by the more CO_2-intensive value chains in lower-income member states. Estonia, with its' high levels of shale oil use, is a case in point.

These results show an *ex ante* evaluation of a stylized EU ETS. Realized outcomes may have differed as the initial phases of the EU ETS were fraught by a range of implementation issues and many permits were allocated free of charge. The policy also did not apply uniformly within sectors, but instead targeted larger installations. A large literature documents these and evaluates the realized effects of the EU ETS (Ellerman et al., 2016; Martin et al., 2016). Despite the stylized nature of this scenario, my results suggest one feature of European carbon prices which has received less attention—the possibly regressive effects across EU consumers, with a disproportionate cost to those living in Eastern European and Baltic member states. This is in line with recent estimates by Feindt et al. (2021) who also find especially large welfare losses for consumers in Eastern Europe.

[18] The EU ETS covered about half of CO_2 emissions. To emulate the intended sector targeting, I apply the carbon price to the following WIOD sectors: "Electricity, Gas and Water Supply", "Mining and Quarrying", "Pulp, Paper, Printing and Processing", "Coke, Refined Petroleum and Nuclear Fuel", "Chemicals and Chemical Products", "Other Non-Metallic Mineral", and "Basic Metals and Fabricated Metal".

[19] The EU ETS price fluctuated around 20-25 EUR per ton throughout 2005. Of 28 EU members in 2018, my sample contains 27. Bulgaria and Romania joined in 2007 and are included. So is the UK, which left in 2020. Only Croatia, which joined in 2013, is not included. Non-EU participants Iceland, Liechtenstein and Norway are not in the sample.

4.3. Scenario 3: A Border Carbon Adjustment (BCA) in the EU

An important concern about carbon pricing is that it may weaken the competitiveness of domestic industries relative to foreign competitors subject to less stringent climate policy. This could cause carbon leakage—emissions simply move abroad instead of being avoided altogether (Levinson and Tayler, 2008; Aichele and Felbermayr, 2015; Fowlie et al., 2016). One answer to these concerns are Border Carbon Adjustments (BCA), which levy tariffs on the emissions content of imports that do not face a carbon price at home (Felder and Rutherford, 1993), complemented by appropriate rebates for exports. In theory, BCA are an elegant solution to the problem of carbon leakage (Markusen, 1975; Hoel, 1996) and they feature in major policy proposals, including those by the Climate Leadership Council for the United States[20] and the European Union's Green Deal[21]. Despite their theoretical and political appeal, we know little about the distributional effects of BCA across income groups. My framework combines distributional welfare analysis with differentiated goods trade and global value chains, making it possible to explore the distributional effects of BCA.

I consider a BCA to complement a carbon price of 30 USD per ton in the EU[22]. The baseline scenario is a uniform carbon price of 30 USD per ton on all CO_2 emissions in the entire EU. A second scenario adds to that a BCA—a carbon tariff on untaxed emissions imported into the EU and a tax exemption for exported emissions. Figure 5a shows the net effect of BCA, which is difference between the two scenarios. The consumer cost of the BCA is rather small and is distributed with an inverse U-shape across the 490 million EU residents. The largest cost falls on consumers at the bottom of the EU income distribution, equivalent to losing 0.5% of expenditure. Yet, BCA appears close to distributionally neutral, with a Suits Index close to 0, as shown in row (5) of Table 2.

Figure 5b shows that the distribution within countries is again rather flat and has a mild inverted

[20] The Four Pillars of our Carbon Dividends Plan, https://clcouncil.org/our-plan/

[21] EU Green Deal - Roadmap and key actions, https://ec.europa.eu/info/files/annex-roadmap-and-key-actions_en

[22] In the analysis of the EU ETS, I limited carbon pricing to emissions in sectors initially targeted by the EU ETS. Here I consider BCA to complement a domestic carbon price covering all sectors. The results are qualitatively similar—albeit with smaller costs—for a BCA limited to EU ETS sectors.

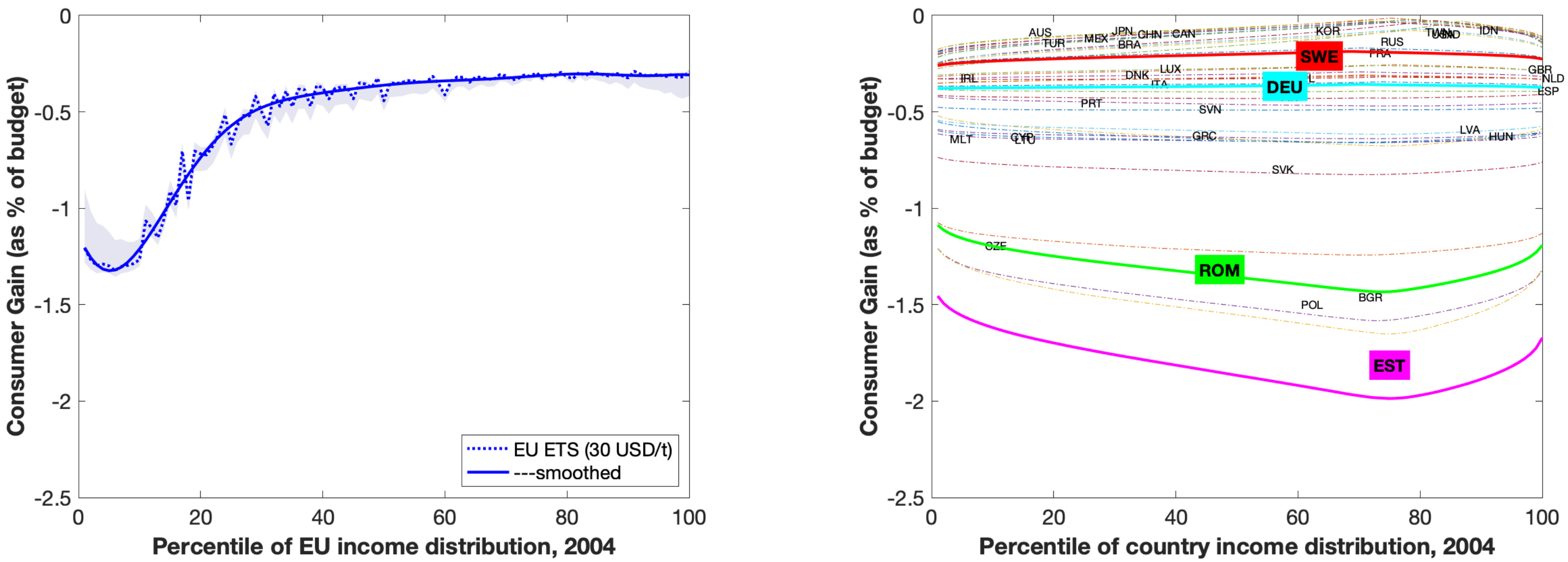
U-shape—consumers with the highest and lowest incomes incur the largest cost. This pattern might be due to both groups consuming larger shares of imported goods which experience a price increase due to BCA. At the bottom of the income distribution these could be imported necessities (e.g. textiles from India), while at the top these could be imports with relatively higher income elasticities (e.g. textiles from the United States). Overall, the cost of BCA varies only modestly, both within countries and between them. This may be due to a relatively similar composition of imports by different EU countries and income groups.

In sum, my simulations suggest a modest and distributionally neutral cost of BCA. While I focus on the distributional effects of BCA, my simulations also confirm the potential to reduce leakage, which is in line with the previous literature[23]. I estimate that complementing the EU-wide carbon price with a BCA would have reduced global CO_2 emissions by an additional 0.7Gt compared to a global baseline of around 18Gt.

[23]CGE models suggest that BCA have the potential to significantly reduce leakage (e.g. Elliott et al., 2010; Böhringer et al., 2016a,b) and shift the burden of emission reduction to countries without domestic carbon prices (Aldy and Pizer, 2015; Böhringer et al., 2018). Using trade gravity approaches, Aichele and Felbermayr (2015) predict significant leakage in absence of BCA and Larch and Wanner (2017) estimate that carbon tariffs somewhat reduce leakage while imposing a net welfare loss on representative consumers in developing countries.

Figure 4: EU Emission Trading System of 30 USD per ton - Consumer cost

(a) EU-wide distribution **(b)** Within-country distribution

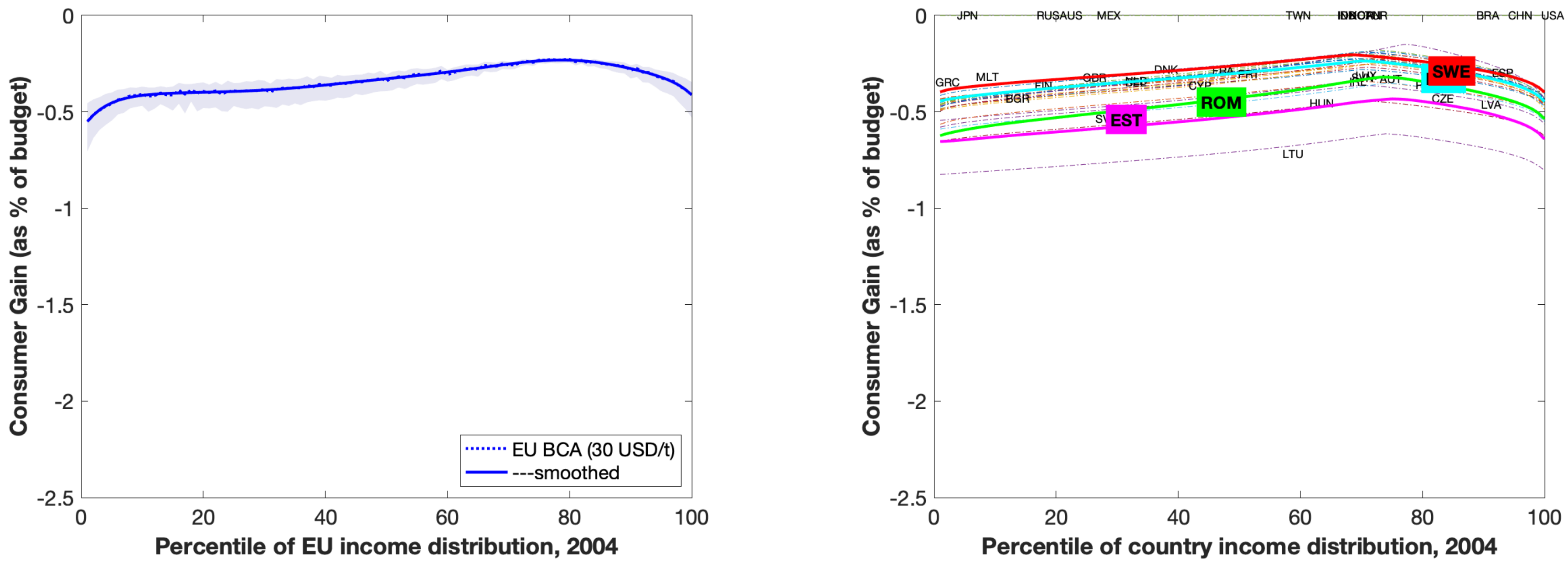


Notes: This figure shows the distribution of the consumer welfare effect under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to the EU ETS target sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution, both EU-wide (Panel a) and within each of the 27 EU countries among the 40 WIOD countries (Panel b) in 2004. Otherwise equivalent to Figure 1 (Panel a) and Figure 2 (Panel b).

Figure 5: EU Border Carbon Adjustment of 30 USD per ton - Consumer cost

(a) EU-wide distribution

(b) Within-country distribution



Notes: Consumer welfare effect under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to all sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution, both EU-wide (Panel a) and within each of the 27 EU countries among the 40 WIOD countries (Panel b) in 2004. Otherwise equivalent to Figure 1 (Panel a) and Figure 2 (Panel b).

5. Robustness

My simulations rely on a number of assumptions outlined in Section 2 and parameters estimated in Section 3, which deserve probing.

5.1. Consistency with consumer survey data

On the demand side, I follow Fajgelbaum and Khandelwal (2016) in identifying global demand system parameters from aggregate trade flows. The within-country distribution is extrapolated based on income elasticities estimated from aggregate expenditure patterns[24]. Simply put, because richer countries buy more textiles from the United States and fewer textiles from India, I expect consumers within countries to follow a similar pattern. To test this rather strong assumption, I compare my estimates to consumer survey data which is commonly used in single-country studies. Figure 9a compares my estimates of the consumer cost of carbon pricing across income groups with survey-based estimates for China, India, Germany, Sweden, and the USA[25]. I focus on the initial incidence, the cost of introducing the first 1 USD per ton of CO_2. The solid lines show estimates based on my structural demand model. The dotted lines show estimates based on consumer surveys. While there are some differences between the two approaches—notably the average emissions intensities differ because survey data does not single out imports—the comparison is reassuring. The two different approaches yield similar estimates of the cost distribution within countries as well as the differences between. Still, the demand system I estimate might be a better fit for some countries than others. In any case, given the dominance of between-country differences, which are entirely based on observed data in my framework, any potential bias in within-country estimates is unlikely to significantly alter the main results.

[24] This could be avoided with harmonized micro-data from all countries capturing consumption at different income levels and separating goods by origin. I am not aware of such data.

[25] Data from the Consumer Expenditure Survey (USA, 2005), EU Household Budget Survey (DEU/SWE, 2005), and the World Bank Global Consumption Database (CHN/IND, 2005-10). Consumption categories (600+ for USA, 106 for CHN/IND, 59 for DEU/SWE) are hand-matched to the 35 WIOD sectors

5.2. Alternative input-output data (Eora)

The results presented above are calibrated using the World Input-Output Database (WIOD). WIOD provides data on 35 sectors in 40 countries (plus RoW). WIOD is one of the most commonly used sources for multi-regional input-output (MRIO) data, mainly due to the its' harmonized and symmetric structure and relative reliability of data. But WIOD is also subject to a number of limitations. I thus replicate my headline results, this time calibrating my model using the symmetric and harmonized version of Eora (Eora 26). Eora covers 26 sectors in 189 countries as recently as 2015. The improved geographic coverage in Eora comes at the cost of a loss of sectoral granularity and more frequent data interpolation, although both data sources have been shown to largely overlap (Moran and Wood, 2014).

Figure 9b compares estimates using Eora data to those using WIOD, both simulating the incidence of a global carbon price of 30 USD per ton at the end of 2004. WIOD results (blue) are those from Figure 1. Eora results (red) are simulated using all 189 countries but the graph is limited to consumers from the same 40 countries in WIOD. The two sets of results rely on entirely separate estimates of demand and production elasticities, country-sector emissions and trade flows. Level differences are largely due to the more comprehensive emissions accounts in Eora. WIOD reports CO_2 emissions from fossil fuel combustion. Eora reports six greenhouse gases[26] emitted from a larger range of activities including land use. Reassuringly, the resulting cost distribution is very similar, both showing the same steep fall between the 60th and 90th percentiles and costs that are about twice as large for the bottom half of the income distribution than for the top 20 percent. Interestingly, the lower end of the income distribution looks more flat when using Eora while it showed a slight progressivity when using WIOD, possibly due to the inclusion of non-CO_2 greenhouse gases such as methane, which are more common in necessity and subsistence goods such as food.

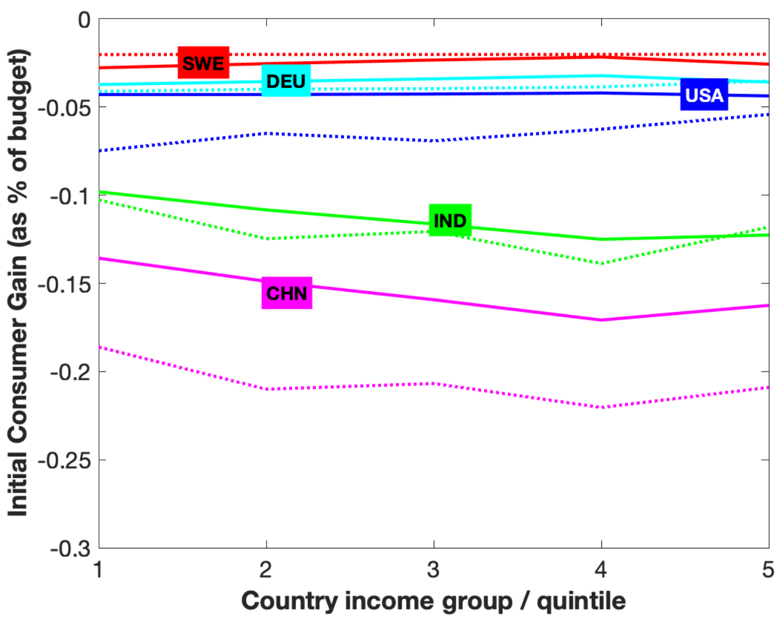
Another drawback of WIOD is data availability. WIOD covers a large share of the world

[26] Eora includes six Kyoto gases following the PRIMAP-hist database: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), hydrofluorocarbons (HFCs), and perfluorocarbons (PFCs). Results look similar when restricted to CO_2 emissions from fossil-fuel combustion as reported by the IEA.

economy—including the entirety of the EU as well as the United States, China, India and a number of other countries—but far from all. As a consequence, Figure 1 is limited to circa 4.2 out of the over 7 billion people worldwide. Eora meanwhile has data, though of mixed quality, for 189 countries and up to 2015. Appendix Figure 12 plots the global consumer cost of a global carbon price of 30 USD per ton across all 189 countries in 2015. The pattern is again similar.

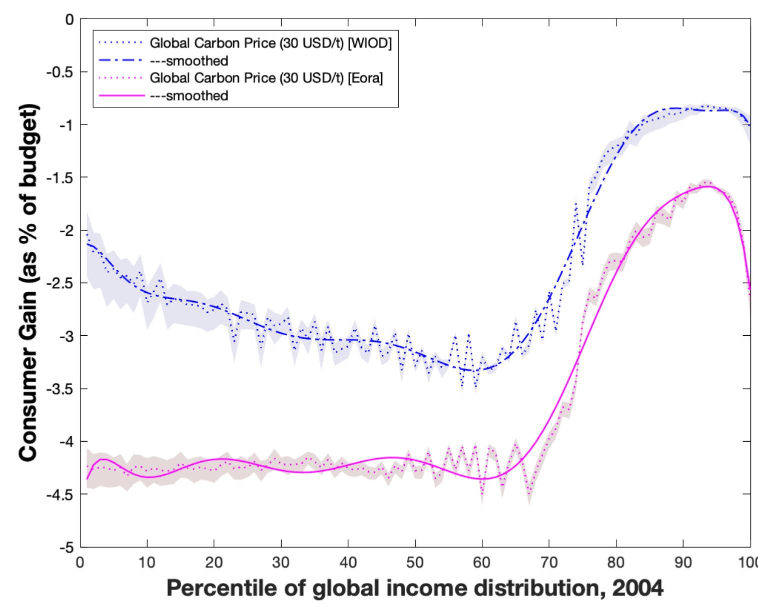
Figure 6: Robustness of main results to alternative data sources

(a) Comparison to consumption survey data



Notes: Comparison of initial incidence (first 1 USD/t) of carbon pricing estimated with the global demand system in this article [solid lines] and estimates from household consumption survey data hand-matched to WIOD sectors [dotted lines]. Survey data from the Consumer Expenditure Survey (USA, 2005), EU Household Budget Survey (DEU + SWE, 2005), and the World Bank Global Consumption Database (CHN + IND, 2005-10). The horizontal axis shows income groups (quintiles for DEU/SWE/USA; World Bank groupings ”Lowest”/”Low”/”Middle”/”Average”/”High” for CHN/IND). The vertical axis shows the relative exposure of consumers in each decile to the first marginal USD of carbon pricing as share of expenditure, equivalent to CO_2 per USD of consumption.

(b) Comparison to alternative input-output data (Eora)



Notes: Comparison of simulation results using WIOD data (used throughout this article) and Eora data. Both show the simulated consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004. WIOD results are the same as shown in Figure 1. Eora results [right axis] are based on newly estimated model parameters and new input-output data, with a carbon price applied to all 189 Eora countries and all greenhouse gases in the Kyoto classification, emitted from a range of activities (including land use). Both shown for subset of 40 countries in WIOD.

5.3. Sensitivity of results to parameter choices

I have shown above that the global demand model estimated from bilateral trade flows approximates demand patterns as observed in consumption survey data reasonably well. And we have seen that the main results on the global consumer incidence of carbon pricing replicate when using an entirely different data source, Eora rather than WIOD, along with a new set of parameter estimates. Still, we may be concerned that the approach to estimating parameters could be biased in both cases. Table 3 thus performs further sensitivity analysis, shown also in Appendix Figure 9.

On the demand side, while panel (a) of Figure 6 shows that incidence patterns simulated by the model are similar to those based on consumer expenditure data in multiple countries, this could mask underlying biases. I thus test the sensitivity of the main results to the choice of demand elasticities. Row (1) of Table 3 reproduces the global incidence of a uniform carbon price of 30 USD per ton shown in Table 2 and Figure 1. A recent paper by Borusyak and Jaravel (2018) claims that the framework by Fajgelbaum and Khandelwal (2016) used here may bias estimates of income elasticities and that trade exposure is instead relatively neutral across the income distribution, at least in the United States. Row (2) shows that the cost of carbon pricing across global income quintiles remains similar when we assume homothetic demand within countries by setting all income semi-elasticities $\beta_i^s = 0$. This is in line with the above finding that the global incidence of carbon pricing is largely driven by between-country differences. We may also be concerned that the degree of demand substitution estimated from bilateral trade costs may be exaggerated. Row (3) shows results when demand is homothetic and demand substitution is switched off, by setting elasticities $\gamma^s = 0$. Estimates are then entirely based on country-aggregate demand patterns observed in the data. Again, the global consumer incidence of carbon pricing looks similar, though it appears that non-homothetic demand and demand substitution somewhat soften the regressivity, as the Suits Index falls further from -0.18 to -0.23 without them.

On the supply side, we may worry that the gravity approach based on iceberg trade costs, proxied by bilateral distance, produces biased estimates of substitution elasticities. The magnitude of trade elasticities and the best way to estimate them are subject to on-going debate in the trade literature

Table 3: Sensitivity of main results to parameter estimates - Global price of 30 USD per ton

	Welfare Effect (as % of budget)						Pro-/regressive (p/r)	
	Q1	Q2	Q3	Q4	Q5	Total	Linear	Suits
(1) Scenario 1: Global Price	**-2.59**	**-2.96**	**-3.19**	**-2.05**	**-0.92**	**-1.16**	**0.66** (r)	**-0.18** (r)
Demand parameters:								
(2) [homothetic demand]	-3.04	-3.25	-3.32	-2.09	-0.84	-1.11	0.77 (r)	-0.22 (r)
(3) [homothetic & static]	-3.45	-3.65	-3.72	-2.32	-0.9	-1.21	0.87 (r)	-0.23 (r)
Production parameters:								
(4) [doubled CES elasticities]	-2.43	-2.78	-3.00	-1.96	-0.89	-1.12	0.62 (r)	-0.17 (r)
(5) [halved CES elasticities]	-2.65	-3.03	-3.26	-2.09	-0.93	-1.18	0.68 (r)	-0.18 (r)
(6) [C&P 2015 elasticities]	-2.47	-2.83	-3.05	-1.98	-0.9	-1.13	0.63 (r)	-0.18 (r)
(7) [no input substitution]	-3.04	-3.47	-3.73	-2.41	-1.09	-1.37	0.78 (r)	-0.18 (r)

Notes: Comparison of consumer cost under different assumptions regarding income and substitution elasticities of demand and input substitution in production. All show smoothed versions of the consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004. (1) Scenario 1: Baseline results reported in Table 2. (2) [homothetic demand]: assumes homothetic demand within countries, setting all $\beta_i^s = 0$. (3) [homothetic & static]: Homothetic demand with no substitution, $\gamma^s = 0$, based on country-average expenditure shares observed in the data. (4) [doubled CES elasticities]: Uses twice the estimated CES production elasticities σ_s. (5) [halved CES elasticities] Uses twice the estimated CES production elasticities σ_s. (6) [C&P 2015 elasticities]: Uses elasticities for traded sectors estimated by Caliendo and Parro (2015), Table 1. (7) [no input substitution] Switches off input substitution entirely, maintaining original value chain structures observed in the data.

(see for example Caliendo and Parro, 2015). Table 3 shows that my results are not especially sensitive to the choice of CES elasticities. Row (4) assumes a higher degree of substitution, by doubling all estimated elasticities σ_s. Row (5) in turn halves them. Row (6) uses trade price elasticities estimated in Caliendo and Parro (2015), which are identified from panel variation in tariff rates. That version also switches off cross-border substitution among non-tradeable sectors (e.g. electricity) entirely. Finally, row (7) switches off all input substitution, maintaining the structure of value chains observed in the data.

Table 3 shows that, while estimated magnitudes may change somewhat depending on the choice of model parameters, the relative cost distribution across world income groups remains largely unchanged.

6. Conclusion

Using a model of global consumer demand and production value chains, parameterized using trade data, I estimate the global consumer cost of carbon pricing. The price effects following a global uniform carbon price are globally regressive. While within-country effects range from moderately progressive to moderately regressive, the global regressivity is driven mainly by differences between countries due to more carbon-intensive value chains in lower income countries. The result is overturned by national carbon dividends, which redistribute carbon pricing revenue equally among consumers within each country. The net effect becomes strongly progressive within countries and globally, even without transfers between countries. And, as I show, the benefits from reduced climate damage are likely to be progressive as well.

Similar results apply when pricing carbon in the EU. Price effects from the EU ETS introduced in 2005 may have been regressive, driven again by differences between countries, with especially high costs to consumers in Eastern European and Baltic member states. Meanwhile, a hypothetical Border Carbon Adjustment to complement an EU-wide carbon price generates rather low costs that are neutrally distributed.

I show that my findings replicate with alternative data, that model projections match well the evidence from country-level consumer surveys, and that the headline results are robust to alternative parameter choices. Still, my results are subject to limitations. In particular, I exclude potentially important effects, including endogenous price adjustments under imperfect competition and income effects from shifting trade patterns, which may alter the global effects of carbon pricing.

Despite these limitations, my results support the notion that carbon pricing, when designed appropriately, can be a progressive policy. When paired with carbon dividends at the national level, carbon pricing has progressive effects that disproportionately benefit consumers with lower incomes, both within countries and worldwide.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hémous, D. (2012a). The environment and directed technical change. *American Economic Review*, 102(1):131–166.

Acemoglu, D., Carvalho, V., Ozdaglar, A., and Tahbaz-Salehi, A. (2012b). The network origins of aggregate fluctuations. *Econometrica*, 80(5):1977–2016.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the Auto industry. *Journal of Political Economy*, 124(1):1–51.

Aichele, R. and Felbermayr, G. (2015). Kyoto and carbon leakage: An empirical analysis of the carbon content of bilateral trade. *Review of Economics and Statistics*, 97(1):104–115.

Aldy, J. and Pizer, W. (2015). The competitiveness impact of climate change mitigation policies. *Journal of the Association of Environmental and Resource Economists*, 2(4):565–595.

Anderson, J. (1979). A theoretical foundation for the gravity equation. *American Economic Review*, 69(1):106–116.

Anderson, J. and Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1):170–192.

Armington, P. (1969). A theory of demand for products distinguished by place of production. *IMF Staff Papers*, 16(1):159–178.

Barbiero, O., Farhi, E., Gopinath, G., and Itskhoki, O. (2019). The macroeconomics of border taxes. *NBER Macroeconomics Annual*, 33(1):395–457.

Böhringer, C., Carbone, J., and Rutherford, T. (2016a). The strategic value of carbon tariffs. *American Economic Journal: Economic Policy*, 8(1):28–51.

Böhringer, C., Carbone, J., and Rutherford, T. (2018). Embodied carbon tariffs. *Scandinavian Journal of Economics*, 120(1):183–210.

Böhringer, C., Müller, A., and Schneider, J. (2016b). Carbon tariffs revisited. *Journal of the Association of Environmental and Resource Economists*, 2(4):629–672.

Borusyak, A. and Jaravel, X. (2018). The distributional effects of trade: Theory and evidence from the united states. Unpublished manuscript available at ssrn 3269579., Ptanford University and LSE.

Burke, M., Hsiang, S., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527:235–239.

Caliendo, L. and Parro, F. (2015). Estimates of the trade and welfare effects of NAFTA. *Review of Economic Studies*, 82:1–44.

Caron, J. and Fally, R. (2018). Per capita income, consumption patterns, and CO2 emissions. NBER Working Paper 24923, National Bureau of Economic Research.

Chepeliev, M., Osorio-Rodarte, I., and van der Mensbrugghe, D. (2021). Distributional impacts of carbon pricing policies under the paris agreement: Inter and intra-regional perspectives. *Energy Economics*, 102:105530.

Copeland, B. and Taylor, M. (1994). North-South tade and the environment. *Quarterly Journal of Economics*, 109(3):755–787.

Datta, A. (2010). The incidence of fuel taxation in India. *Energy Economics*, 32(1):S26–S33.

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system. *American Economic Review*, 70:312–326.

Dell, M., Jones, B., and Olken, B. (2012). Temperature shocks and economics growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dorband, I., Jakob, M., Kalkuhl, M., and J.C., S. (2019). Poverty and distributional effects of carbon pricing in low- and middle-income countries—a global comparative analysis. *World Development*, 115:246–257.

Drupp, M. A., Kornek, U., Meya, J. N., Sager, L., et al. (2021). Inequality and the environment: The economics of a two-headed hydra. Technical report, CESifo.

Ellerman, A. and Buchner, B. (2007). The European Union Emissions Trading System: Origins, allocation, and early results. *Review of Environmental Economics and Policy*, 1(1):66–87.

Ellerman, A., Marcantonini, C., and Zaklan, A. (2016). The European Union Emissions Trading System: Ten years and counting. *Review of Environmental Economics and Policy*, 10(1):89–107.

Elliott, J., Foster, I., Kortum, S., Munson, T., F., C., and Weisbach, D. (2010). Trade and carbon taxes. *AER: Papers & Proceedings*, 100:465–469.

Fajgelbaum, P. and Khandelwal, A. (2016). Measuring the unequal gains from trade. *Quarterly Journal of Economics*, 131(3):1113–1180.

Feenstra, R. and Romalis, J. (2014). International prices and endogenous quality. *Quarterly Journal of Economics*, 129(2):477–527.

Feindt, S., Kornek, U., Labeaga, J. M., Sterner, T., and Ward, H. (2021). Understanding regressivity: Challenges and opportunities of european carbon pricing. *Energy Economics*, 103:105550.

Felder, S. and Rutherford, T. (1993). Unilateral CO2 reductions and carbon leakage: The consequences of international trade in oil and basic materials. *Journal of Environmental Economics and Management*, 25(2):162–176.

Fowlie, M., Requant, M., and Ryan, S. (2016). Market-based emissions regulation and industry dynamics. *Journal of Political Economy*, 124(1):249–302.

Fullerton, D. and Heutel, G. (2007). The general equilibrium incidence of environmental taxes. *Journal of Public Economics*, 91:571–591.

Ganapati, S., Shapiro, J., and Walker, R. (2019). Energy cost pass-through in US manufacturing: Estimates and implications for carbon taxes. *American Economic Journal: Applied Economics*, forthcoming:1–53.

Genty, A., Arto, I., and Neuwahl, F. (2012). Final database of environmental satellite accounts: Technical report on their compilation. Technical Report 4, WIOD.

Gonzalez, F. (2012). Distributional effects of carbon taxes: The case of Mexico. *Energy Economics*, 34(6):2102–2115.

Goulder, L., Hafstead, M., Kim, G., and Long, X. (2019). Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs? *Journal of Public Economics*, 175:44–64.

Grainger, C. and Kolstad, C. (2010). Who pays a price on carbon? *Environmental and Resource Economics*, 46:359–376.

Hafstead, M. A., Williams III, R. C., and Chen, Y. (2022). Environmental policy, full-employment models, and employment: A critical analysis. *Journal of the Association of Environmental and*

Resource Economists, 9(2):199–234.

Hassett, K., Mathur, A., and Metcalf, G. (2009). The incidence of a U.S. carbon tax: A lifetime and regional analysis. *Energy Journal*, 30(2):155–177.

Head, K. and Mayer, T. (2014). Gravity equations: Workhorse, toolkit, and cookbook. *Handbook of International Economics*, 4:131–195.

Hoel, M. (1996). Should a carbon tax be differentiated across sectors? *Journal of Public Economics*, 59:17–32.

Larch, M. and Wanner, J. (2017). Carbon tariffs: An analysis of the trade, welfare, and emission effects. *Journal of International Economics*, 109:195–213.

Leontief, W. (1970). Environmental repercussions of the economic structure: An input-output approach. *Review of Economics and Statistics*, 52(3):262–271.

Levinson, A. (2009). Technology, international trade, and pollution from US manufacturing. *American Economic Review*, 99(5):2177–2192.

Levinson, A. and O'Brien, J. (2019). Environmental Engel curves: Indirect emissions of common air pollutants. *Review of Economics and Statistics*, 101(1):121–133.

Levinson, A. and Tayler, M. (2008). Unmasking the Pollution Haven Effect. *International Economic Review*, 49(1):223–254.

Markusen, J. (1975). International externalities and optimal tax structures. *Journal of International Economics*, 5(1):15–29.

Martin, R., Muûls, M., and Wagner, U. (2016). The impact of the European Emissions Trading Scheme on regulated firms: What is the evidence after ten years? *Review of Environmental Economics and Policy*, 10(1):129–148.

Mehling, M., Metcalf, G., and Stavins, R. (2018). Linking climate policies to advance global mitigation. *Science*, 359(6379):997–998.

Metcalf, G. (2009). Designing a carbon tax to reduce U.S. greenhouse gas emissions. *Review of Environmental Economics and Policy*, 3(1):63–83.

Moran, D. and Wood, R. (2014). Convergence between the eora, wiod, exiobase, and openeu's consumption-based carbon accounts. *Economic Systems Research*, 26(3):245–261.

Muellbauer, J. (1975). Aggregation, income distribution and consumer demand. *Review of Economic Studies*, 52:525–543.

Novy, D. (2013). International trade without CES: Estimating translog gravity. *Journal of International Economics*, 89:271–282.

Peter, A. and Ruane, C. (2018). The aggregate importance of intermediate input substitutability. Unpublished manuscript, Stanford University and IMF.

Poterba, J. (1991). Is the gasoline tax regressive? *Tax Policy and the Economy*, 5:145–164.

Rausch, S., Metcalf, G., and Reilly, J. (2011). Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics*, 33(1):S20–S33.

Ricke, K., Drouet, L., Caldeira, K., and Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, 8:895–900.

Sager, L. (2019). Income inequality and carbon consumption: Evidence from Environmental Engel curves. *Energy Economics*, 84:104507.

Shah, A. and Larsen, B. (1992). Carbon taxes, the Greenhouse effect, and developing countries.

Working Papers 957, World Bank.

Shapiro, J. (2016). Trade costs, CO2, and the environment. *American Economic Journal: Economic Policy*, 8(4):220–254.

Stern, D. (2012). Interfuel substitution: A meta-analysis. *Journal of Economic Surveys*, 26(2):307–331.

Sterner, T. (2012). Distributional effects of taxing transport fuel. *Energy Policy*, 41:75–83.

Suits, D. (1977). Measurement of tax progressivity. *American Economic Review*, 67(4):747–752.

West, S. and Williams, R. (2004). Estimates from a consumer demand system: Implications for the incidence of environmental taxes. *Journal of Environmental Economics and Management*, 47(3):535–558.

Whalley, J. and Wigle, R. (1991). The international incidence of carbon taxes. In Dornbusch, R. and Poterba, J., editors, *Global Warming: Economic Policy Responses*, chapter 7, pages 233–263. MIT Press, London, United Kingdom.

Williams, R., Gordon, H., Burtraw, D., Carbone, J., and Morgenstern, R. (2015). The initial incidence of a carbon tax across income groups. *National Tax Journal*, 68(1):195–214.

World Bank and Ecofys (2020). *State and Trends of Carbon Pricing 202 (May).* World Bank, Washington, D.C.

For Online Publication

The Global Consumer Incidence of Carbon Pricing: Evidence from Trade

APPENDIX

A. Modeling the global cost of carbon pricing

This Appendix provides a more detailed discussion of the model and key assumptions.

A.1. Demand: A global Almost Ideal Demand System

Much of the approach on the demand side follows Fajgelbaum and Khandelwal (2016) and is repeated here for completeness. The core of the analysis is a global Almost Ideal Demand System (AIDS) describing consumer preferences. AIDS was first proposed by Deaton and Muellbauer (1980) and is characterized as follows.

Assumption A1 (AIDS Consumer Preferences) *Demand of consumer h, with budget x_h, over goods j is characterized by the family of log price-independent generalized (PIGLOG) preferences proposed by Muellbauer (1975) with indirect utility:*

$$v(x_h, \mathbf{p}) = F\left[\left(\frac{x_h}{a(\mathbf{p})}\right)^{\frac{1}{b(\mathbf{p})}}\right] \tag{11}$$

$F(.)$ is increasing and well-behaved, and the price aggregators are:

$$a(\mathbf{p}) = \exp\left(\underline{\alpha} + \sum_{j=1}^{J} \alpha_j \log\left(p_j\right) + \frac{1}{2}\sum_{j=1}^{J}\sum_{j'=1}^{J} \gamma_{jj'} \log\left(p_j\right)\log\left(p_{j'}\right)\right) \tag{12}$$

$$b(\mathbf{p}) = \exp\left(\sum_{j=1}^{J} \beta_j \log\left(p_j\right)\right) \tag{13}$$

A consumer h chooses between J goods and has indirect utility $v(x_h, \mathbf{p})$ which depends on her total expenditure budget x_h and the vector of prices $\mathbf{p}$. The additional assumptions on price aggregators $a(\mathbf{p})$ and $b(\mathbf{p})$ close the description of the AIDS model. The AIDS model can be summarized using the expenditure share that consumer h, with budget x_h, devotes to good j:

$$s_j(\mathbf{p}, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{j'=1}^{J} \gamma_{jj'} \log\left(p_{j'}\right) + \beta_j \log\left(\frac{x_h}{a(\mathbf{p})}\right) \tag{14}$$

Expenditure of h on good j depends on preferences for good j (α_j), prices of all goods j' ($p_{j'}$) and individual real income ($\frac{x_h}{a(\mathbf{p})}$). Key elasticities are the cross-price elasticities between goods j and j' ($\gamma_{jj'}$) and income (semi)-elasticities for each good j (β_j). Positive good-specific income elasticities ($\beta_j > 0$) mean that j is a luxury good (and a necessity if $\beta_j < 0$). Parameters are restricted to $\sum_{j=1}^{J} \alpha_j = 1$, $\sum_{j=1}^{J} \beta_j = \sum_{j=1}^{J} \gamma_{jj'} = 0$ and $\gamma_{jj'} = \gamma_{jj'}$ for all j, j'.

While allowing for heterogeneity of expenditure patterns across the income distribution, these expenditure shares are still conveniently aggregated via an inequality-adjusted version of average income. The aggregate share that all consumers spend on good j is:

$$S_j = \alpha_j + \sum_{j'=1}^{J} \gamma_{jj'} \log\left(p_{j'}\right) + \beta_j y \tag{15}$$

Aggregate expenditure shares resemble individual ones, but individual income is replaced by inequality adjusted real income $y = \log\left(\frac{\tilde{x}}{a(\mathbf{p})}\right)$. This is the price-adjusted version of the inequality-adjusted mean expenditure $\tilde{x} = \bar{x}e^{\Sigma}$ where $\Sigma = \mathrm{E}\left[\frac{x_h}{\bar{x}}\log\left(\frac{x_h}{\bar{x}}\right)\right]$ is the Theil index of income inequality.

Thanks to this aggregation property, it is possible to estimate demand parameters from aggregate expenditure shares. I do so using between-country trade flows, following closely the method proposed by Fajgelbaum and Khandelwal (2016). Once parameterized, the demand system allows for simulation of the consumption distribution within each country around aggregate expenditure levels. Specifically, I allow average preferences for goods j (α_j) to differ between countries, but assume that consumers in all countries share the same price and income elasticities ($\gamma_{jj'}$ and β_j).

Derivation of Welfare Effect, Proposition 1:

We consider the change in the log of indirect utility of consumer h due to infinitesimal changes in log prices $\hat{p}_j = dlog(p_j)$ for all J goods and the log of expenditure $\hat{x}_h = dlog(x_h$. Fajgelbaum and Khandelwal (2016) show that the change in indirect utility is:

$$\hat{v}_h = \sum_{j=1}^{J} \frac{\partial \log\left(v(x_h, \mathbf{p})\right)}{\partial \log\left(p_j\right)} \hat{p}_j + \frac{\partial \log\left(v(x_h, \mathbf{p})\right)}{\partial \log\left(x_h\right)} \hat{x}_h \tag{16}$$

Equivalent variation is then defined as the change in log expenditures, $\hat{\omega}_h$ that would lead to the indirect utility change $\hat{v}_h$ at constant prices:

$$\hat{v}_h = \frac{\partial \log\left(v(x_h, \mathbf{p})\right)}{\partial \log\left(x_h\right)} \hat{\omega}_h \tag{17}$$

After applying Roy's identity $\left(y_{h,j} = -\frac{\partial v(.)/\partial p_j}{\partial v(.)/\partial x_h}\right)$, the individual welfare effect can be separated into three elements:

$$\begin{aligned} \hat{\omega}_h &= \sum_{j=1}^{J} \left(-\hat{p}_j\right) s_{j,h} + \hat{x}_h \\ &= \sum_{j=1}^{J} \left(-\hat{p}_j\right) S_j + \qquad \sum_{j=1}^{J} \left(-\hat{p}_j\right)\left(s_{j,h} - S_j\right) + \qquad \hat{x}_h \\ &= \hat{W} + \qquad\qquad\qquad \hat{\psi}_h + \qquad\qquad\qquad \hat{x}_h \end{aligned} \tag{18}$$

Here, $\hat{x}_h$ is the income effect, $\hat{W}$ is the aggregate expenditure effect and $\hat{\psi}_h$ is the individual expenditure effect of consumer h. $\hat{\psi}_h$ captures that consumers with different income levels may be differentially affected by price changes because they have a different expenditure composition.

Using the expenditure shares under the AIDS demand structure, we can use the fact that $s_{j,h} - S_j = \beta_j \log\left(\frac{x_h}{\tilde{x}}\right)$, to re-write the individual expenditure effect:

$$\hat{\psi}_h = -\left(\sum_{j=1}^{J} \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) \tag{19}$$

This gives the welfare change of consumer h as stated in Proposition 1:

$$\hat{\omega}_h = \hat{W} - \left(\sum_{j=1}^{J} \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) + \hat{x}_h \tag{20}$$

A.2. Supply: Input substitution in global value chains

The supply side is characterized by a set of Constant Elasticity of Substitution (CES) production functions.

Assumption A2 (CES Production Functions) *Assume that all producers in each sector j have an identical Constant Elasticity of Substitution (CES) production function across K intermediate inputs f_{kj} with prices ρ_{kj}. We further assume perfect competition and constant returns to scale in all sectors. Input choices in each sector are then equivalent to a representative producer minimizing input cost C_j:*

$$min\ C_j = \sum_k \rho_{kj} f_{kj} \quad s.t.\ T_j \left(\sum_k \theta_{kj}^{1/\sigma_j} f_{kj}^{(\sigma_j-1)/\sigma_j}\right)^{\sigma_j/(\sigma_j-1)} = X_j \tag{21}$$

For any level of output X_j, producers minimize input costs C_j. The expenditure share on input k among expenditures for all intermediate inputs is given by:

$$E_{kj} = \frac{\rho_{kj} f_{kj}}{C_j} = \theta_{kj} \rho_{kj}^{(1-\sigma_j)} P_j^{(\sigma_j-1)} \tag{22}$$

The cost share of input k depends on technology factor θ_{kj}, which defines the cost share under equal input prices. E_{kj} is decreasing in the price of k, ρ_{kj}, relative to the input price index $P_j = (\sum_k \theta_{kj} \rho_{kj}^{(1-\sigma_j)})^{1/(1-\sigma_j)}$. Constant returns to scale combined with perfect competition imply that input shares and output prices are independent of final demand. No additional equilibrium price condition is needed.

The CES production technologies translate as follows into the input-output framework, which I use to account for CO_2 emissions and, hence, price changes. Total expenditure on all intermediates by sector j is $C_j = P_j X_j$. All output is used either as intermediate input in another sector or as final consumption, both at the same price. The difference between the final price p_j for one unit of good j and required input expenditures defines the value added share $\kappa_j = \frac{p_j - P_j}{p_j}$, which I assume to be constant throughout. Each dollar value of output in sector j then uses an average amount of dollar value inputs from sectors k, $a_{kj} = E_{kj}(1-\kappa_j)$. This yields a linear relation between input and output in value terms:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{y} \tag{23}$$

Here, $\mathbf{x}$ is the J-vector of aggregate outputs in value terms (elements $p_j X_j$), $\mathbf{A}$ is the $(J \times K = J^2)$-matrix of normalized input requirements a_{kj} and $\mathbf{y}$ the J-vector of final consumption again in value terms (elements $p_j y_j$).

While this linear relationship follows Leontief (1970), it does not require Leontief production technologies. The notable difference is that under CES technologies the relationship is expressed in value terms instead of volume. This is similar to Acemoglu et al. (2012b), who use such a linear mapping to describe the network structure of an economy with Cobb-Douglas technologies[27].

The Direct Requirement matrix $\mathbf{A}$ has elements a_{kj} which show the dollar amount of intermediate input from country-sector k necessary for the production of a dollar of output in country-sector j. Following Leontief (1970), we use $\mathbf{A}$ to describe the relationship between the vector of final goods output $\mathbf{y}$ and total output including intermediates $\mathbf{x}$ as follows:

$$\mathbf{x} = [\mathbf{I} - \mathbf{A}]^{-1}\mathbf{y} = \mathbf{T}\mathbf{y} \tag{24}$$

This relationship yields the Total Requirement matrix $\mathbf{T} = [\mathbf{I} - \mathbf{A}]^{-1}$. Elements of $\mathbf{T}$, t_{kj}, describe the dollar amount of total input from sector k embedded in a dollar of final consumption from sector j, accounting for all upstream processes. Total input requirements are then translated into total emissions intensities:

$$\mathbf{e} = \mathbf{T}'\mathbf{d} \tag{25}$$

The J-vector $\mathbf{d}$ of direct emissions intensities $d_{j=k}$ describes for each sector the CO_2 emissions per dollar output. Element e_j of $\mathbf{e}$ then summarizes the total CO_2 emissions intensity (tons of CO_2 per \$) of final consumption from sector j, including all upstream emissions in sectors k. The effect on final prices due to a price on carbon emissions will be a function of these total emission intensities e_j. When evaluating carbon pricing scenarios, I simulate a new equilibrium input-output structure of the economy ($\mathbf{A}$ and $\mathbf{T}$), which yields a new set of emissions intensities ($\mathbf{e}$). These directly translate into final price changes seen by consumers.

Price dynamics:

For any given input-output structure, the emission intensity e_j of final good j determines its relative price increase when we introduce a price on CO_2 emissions. When no input substitution takes place, this takes the following form[28].

Proposition 3 (Price effect without substitution) *Assume a carbon price τ (in \$ per ton of CO_2) is introduced. Holding constant the structure of value chains $\mathbf{A}$ and hence the total emissions content of goods e_j, this will raise final prices to a new level $p_j^* = (1 + \tau e_j)p_j$.*

This is the price increase predicted by standard MRIO methods that assume fixed proportion production functions (following Leontief, 1970). But I allow producers to substitute intermediate inputs. This alters the structure of value chains and, consequently, emissions intensities e_j. This invites yet further adjustments to inputs until a new equilibrium is reached. I also allow carbon prices to vary by pairs of production (j) and input supply sectors (k).

[27] When technologies are of the Cobb-Douglas variety, C is constant for all price combinations (as in Acemoglu et al., 2012b, and others). I add further flexibility in input substitution by modeling CES technologies, which means that C adjusts when input prices change. This reduces analytical tractability, but adds what I think is important flexibility when analyzing carbon pricing. I approximate the adjustment of inputs recursively as described in Appendix A.3.

[28] It is does not matter where in the supply chain the price on emissions is levied. This could be a consumption tax levied on the final good or emissions pricing at the source. Perfect competition implies that producers will fully pass-through price increases to consumers and competitive firms will internalize carbon prices even if they were to be levied at the point of sale.

Proposition 4 (Price effect with input substitution) *Assume a set of carbon prices $\{\tau_{kj}\}$ on intermediate goods k used in production j is introduced. Given initial input requirements $\{a_{kj}\}$ and direct emissions intensities $\{d_j\}$, the new equilibrium production structure is defined jointly by:*

$$a^*_{kj} = a_{kj}\left(\frac{\left(\sum_i \theta_{ij}(1+\tau_{ij}e^*_i)^{(1-\sigma_j)}\right)^{1/(1-\sigma_j)}}{1+\tau_{kj}e^*_k}\right)^{\sigma_j} \quad \forall k,j \tag{26}$$

$$\mathbf{e}^* = \left[(\mathbf{I}-\mathbf{A}^*)^{-1}\right]'\mathbf{d} \tag{27}$$

Proof. Given the assumed initial price changes to $p^*_k = (1+\tau e_k)p_k$, the new share of inputs k in the expenditure of sector j relative to the old share would become:

$$\frac{E^*_{kj}}{E_{kj}} = (1+\tau e_k)^{(1-\sigma_j)}\left(\frac{P^*_j}{P_j}\right)^{(\sigma_j-1)} \tag{28}$$

Assuming unchanged value-added shares κ_j, we get an updated 'Direct Requirement Matrix' $\mathbf{A}^*$ which has elements:

$$c^*_{kj} = \frac{E^*_{kj}}{E_{kj}}\frac{P^*_j}{1+\tau e_k} = \left(\frac{P^*_j}{1+\tau e_k}\right)^{\sigma_j} c_{kj} \tag{29}$$

This "Direct Requirement Matrix" at new prices now has a slightly different interpretation than the one at original prices. The original "Direct Requirement Matrix" had elements c_{kj} which characterized the dollar value of input required from sector k to produce one dollar value of final output in sector j. Define a new unit of measurement for each sector j, which we shall call "previous dollar value unit" (PDU). One PDU is equal to the amount of good j that could be bought at the original prices. Essentially, I normalize all initial prices to $p_j = 1\ \forall j$. The elements of the new "Direct Requirement Matrix" is then interpreted as follows: After the price change, to generate one PDU of output in sector j we require c^*_{kj} units (in PDU) of intermediate good k.

The "direct emissions intensity" $d^*_j = d_j$ remains unchanged in this step but now also characterizes the direct emissions per PDU output (i.e. the emissions related to the value-added for one unit produced). But of course, the adjustments to input use will themselves change the structure of supply chains and, in consequence, the emissions intensities e_j and prices. I assume throughout that the price of good j used as intermediate inputs is the same as when bought as final good (denoted as k in those cases). Calculating new "total emissions intensities" per PDU should then be $\mathbf{e}^* = (I-\mathbf{A}^*)^{-1}\mathbf{d}$ and the final goods price of j including the carbon price is $1+\tau e^*_j$. The process settles in equilibrium when both these conditions are met. I approximate this new structure numerically as described in A.3. ■

Fuel switching: In my simulations, I allow for substitution between four groups of energy fuels: coal, gas, oil, renewable.

Initial shares of those fuel types in the energy use of country-sectors are from WIOD ('Emissions relevant energy use (in TJ)' [EM table]) and Eora [Eora26 Q-table], grouped together as follows:

To simulate fuel substitution, I rely on pairwise inter-fuel substitution elasticities drawn from the meta analysis by Stern (2012). Specifically, I use sample-size weighted mean values for pairwise shadow elasticities of substitution provided in Table 3 of Stern (2012), using electricity-specific elasticities for all renewables: Coal-Oil ($sigma^{CO} = 1.065$), Coal-Gas ($\sigma^{CG} = 1.426$),

Table 4: Fuel type groupings used in simulations

Fuel Group	WIOD	Eora
Coal	anthracite, lignite, coke	‘coal’
Gas	natural, other gas	‘natural gas’
Oil	gasoline, Diesel, jet kerosene, LFO, HFO, naphtha	‘petroleum’
Other (‘Renewable’)	biogas, bio diesel, electricity, heat production, nuclear, hydropower, geothermal, solar, wind	nuclear, hydroelectric, wind, solar/tide/wave, biomass and waste

Notes: Overview of fuel type groupings used.

Coal-Renewable ($\sigma^{CR} = 0.866$), Oil-Gas ($\sigma^{OG} = 2.022$), Oil-Renewable ($\sigma^{OR} = 1.060$), and Gas-Renewable ($\sigma^{GR} = 1.099$).

Relative price changes of these fuels are based on their global average price (from the BP Statistical Review of World Energy 2017) and CO_2 content (from the IEA 2006 Guidelines on Default Carbon Content Values). Pairwise substitution using the above elasticities yields new simulated fuel shares, holding constant the total energy use per (in TJ) unit of output in each country-sector. The change in fuel shares—weighted by their emissions intensities—is then used to update the direct emissions intensities $\{d_j\}$, to be used in the above described process of intermediate input substitution.

A.3. Numerical approximation of new equilibrium production

I approximate numerically the new equilibrium supply chain structure $\mathbf{A}^*$, emission intensities e_j^* and prices $p_{kj}^* = (1+\tau_{kj}e_j^*)p_{kj}$. I do this using an iterative process with the following steps:

1. Simulate new direct emissions intensities $\{d_j^*\}$ after fuel substitution following the approach described in Appendix A.2.
2. Calculate initial total emissions intensities $\{e_j^*\}$ based on original production $\{c_{kj}\}$ paired with updated direct emissions intensities $\{d_j^*\}$.
3. Calculate initial price changes of intermediate inputs $\hat{\rho}_{kj}^*$ based on $\{e_j^*\}$. In scenarios with differentiated carbon pricing (e.g. Border Carbon Adjustments), only count those emissions from origin sectors $K = S' \times I$ that are being priced in destinations $J = S \times N$.
4. Calculate initial adjustment of input requirements $\{a_{kj}^*\}$ based on these price changes $\hat{\rho}_{kj}^*$.
5. Calculate updated total emissions intensities $\{e_j^*\}$ based on updated production $\{c_{kj}^*\}$ paired with updated direct emissions intensities $\{d_j^*\}$.
6. Repeat the loop through steps 3-5 until the additional adjustments in value chains become negligible, as defined by $\sum \frac{|\Delta a_{kj}^*|}{a_{kj}} < \frac{1}{10{,}000}$.

In all simulations reported in this article, the procedure converges very quickly, taking about 3-10 loops over steps 3-5 to settle in a state where additional rounds of adjustment are negligible.

B. Calibrating the model

This Appendix provides further detail on the estimation of model parameters.

B.1. Demand: Estimating demand system parameters

To identify demand parameters, I follow Fajgelbaum and Khandelwal (2016) in embedding the AIDS demand structure in a multi-sector Armington model of international trade of final goods, allowing for goods within each sector to be differentiated by origin and for cross-country differences in sectoral productivity and trade cost. Essentially, each sector from each country sells a different variety. For WIOD, which has datta on 35 sectors and 40 countries, this translates to 1400 varieties ($J = K = 40 \times 35$).

Consumers in destination country n consume goods from sector s in origin i. To characterize demand responses and welfare effects for households h in country n, I estimate income semi-elasticities (β_i^s) for each of the 1400 varieties, as well as price elasticities. For the latter, I follow Fajgelbaum and Khandelwal (2016) in assuming that there is symmetric substitution within each sector s between goods from different countries i, but no substitution between sectors:

$$\gamma_{ii'}^{ss'} = \begin{cases} -\left(1 - \frac{1}{N}\right)\gamma^s & \text{if } i = i' \text{ and } s = s' \\ \frac{1}{N}\gamma^s & \text{if } i \neq i' \text{ and } s = s' \\ 0 & \text{otherwise} \end{cases} \tag{30}$$

Consumers can substitute textiles from the United States with textiles from India, but they cannot substitute textiles with minerals. To identify the 35 sector-level price elasticity parameters (γ^s), I assume that trade costs between country-pairs (t_{ni}) are of the iceberg variety, implying $p_{ni}^s = t_{ni} p_i^s$.

Specifically, I assume that bilateral trade costs between origin i and destination n are $t_{ni} = d_{ni}^{\rho} \Pi_l \left(g_{l,ni}^{d_l} \right) \eta_{ni}$, where d_{ni} is bilateral distance and ρ is the distance elasticity of trade costs. Other determinants of bilateral trade cost, namely shared borders and language, are in $g_{l,ni}$. These are transformed into regression variables D_{ni} and $G_{l,ni}$ as follows:

$$D_{ni} = ln\left(\frac{d_{ni}}{\overline{d}_n}\right) - \sum_{n'=1}^{N} \left(\frac{Y_{n'}}{Y_W}\right) ln\left(\frac{d_{n'i}}{\overline{d}_{n'}}\right) \tag{31}$$

Following Fajgelbaum and Khandelwal (2016), this yields an estimating equation for aggregate expenditure by consumers in country n on goods from sector s and country i:

$$S_{ni}^s = \frac{Y_i^s}{Y_W} + \alpha_i (S_n^s - S_W^s) - (\gamma^s \rho^s) D_{ni} + \sum_l (\gamma^s d_l^s) G_{l,ni} + (\beta_i^s - \alpha_i \overline{\beta}^s) \Omega_n + \varepsilon_{ni}^s \tag{32}$$

These aggregate expenditure shares (S_{ni}^s) are observed in WIOD (and Eora). Consumers in n buy more goods from sector s in origin country i if that sector is a large relative to the world economy ($\frac{Y_i^s}{Y_W}$) and if consumers in n spend more on goods in sector s relative to the rest of the world (($S_n^s - S_W^s$)). Variation in distance (D_{ni} helps identify price elasticities (γ^s). If trade is more concentrated among less distant country pairs within one sector than another, I estimate the former to face a higher price elasticity of demand.

Variation in the inequality-adjusted mean income of country n relative to the world ($\Omega_n = y_n - \bar{y}_W$) helps identify the income elasticities (β_i^s). If textiles from the United States are consumed more in richer countries, or more unequal countries, than textiles from India, then I estimate the former to have a higher income elasticity. Ω_n is calculated using country-level population and income (GDP) from the Penn World Tables and the Gini index of income inequality from the World Income Inequality Database (WIID). I assume that individual expenditure x_h is proportional to income, i.e. that there is a constant savings rate[29], and that income is log-normally distributed. The Gini index is easily converted into the required Theil index[30]. Following the methodology of Fajgelbaum and Khandelwal (2016), I also proxy for the non-homothetic price index $a(\mathbf{p})$ with a Stone price index for each destination country n using quality-adjusted prices as provided by Feenstra and Romalis (2014).

From the estimation of (32), I identify the following parameter estimates: $\hat{\alpha}_i$, $(\widehat{\beta_i^s - \alpha_i \overline{\beta}^s})$, $\widehat{(\gamma^s \rho^s)}$. A second estimation equation helps to identify the missing parameters $\hat{\overline{\beta}}^s$. I estimate an Engel curve projecting aggregate expenditure shares in country n for sectors s on the inequality-adjusted real income y_n:

$$S_n^s = \alpha^s + \overline{\beta}^s y_n + \varepsilon_n^s \tag{33}$$

This estimation helps to identify what Fajgelbaum and Khandelwal (2016) call the "sectoral betas", the sector average income semi-elasticities, $\overline{\beta}^s$. ε_n^s is the specific taste of importer n for sector s. These estimates $\hat{\overline{\beta}}^s$ together with the estimates of $\hat{\alpha}_i$ from the above gravity estimation are sufficient to identify origin-sector specific income semi-elasticities $\hat{\beta}_i^s$. Finally, to pin down price elasticity parameters $\hat{\gamma}^s$, I follow Novy (2013) (and Fajgelbaum and Khandelwal, 2016) in setting $\rho^s = \rho = 0.177$ for all s.

B.2. Supply: Estimating production function parameters

On the supply side, I again identify the relevant model parameters from trade data—this time from bilateral inter-industry trade. I again derive a simple gravity equation to estimate the production elasticity σ_j for each industry j. CES production implies that producers in industry j spend the following share of their expenditures on intermediate inputs from industry k:

$$E_{kj} = \frac{\rho_{kj} f_{kj}}{P_j X_j} = \theta_{kj} \rho_{kj}^{(1-\sigma_j)} P_j^{(\sigma_j - 1)} \tag{34}$$

I consider bilateral inter-industry trade flows between industry pairs—destination sector s in country n ($J = S \times N$) sources inputs from origin sector s' in country i (in the case of WIOD there are $J \times K = 1400^2 = 1.96$million such pairs). Again, I assume that each sector s' in origin i produces a distinct input variety ($J = S \times I$) and that the market for intermediate goods is perfectly

[29] Basing my analysis on expenditure distributions—sometimes seen as more representative of lifetime income—should make it less likely to find regressive effects of carbon pricing than using annual income (as shown e.g. by Hassett et al., 2009; Grainger and Kolstad, 2010).

[30] Assuming a log-normal distribution of expenditure with variance σ^2, the Theil index is $\sum = \frac{\sigma^2}{2}$ where the relation between σ^2 and the Gini coefficient G is given by $\sigma^2 = 2\left[\frac{G+1}{2}\right]^2$.

competitive. I further assume that prices are the same for goods from sector s whether they are used as intermediates or final goods ($p_i^s = \rho_i^{s'}$) and that traded goods are subject to iceberg trade costs t_{ni} between destination n and origin i, $p_{ni}^s = t_{ni} p_i^s$. Finally, I assume that production functions are identical for each destination sector j across countries n ($\sigma_{n,j} = \sigma_j$ and $\theta_{ni}^{ss'} = \theta_i^{ss'}$, $\forall n$). Each sector s in destination n will then spend the following share on intermediate inputs from sector s' in origin i:

$$E_{ni}^{ss'} = \theta_i^{ss'} (t_{ni})^{(1-\sigma_s)} (p_i^{s'})^{(1-\sigma_s)} (P_n^s)^{(\sigma_s - 1)} \tag{35}$$

In its log-linear version, we obtain the following gravity equation:

$$\begin{aligned} \log\left(E_{ni}^{ss'}\right) &= \log\left(\theta_i^{ss'}\right) + (1-\sigma_s)\log(t_{ni}) + (1-\sigma_s)\log\left(p_i^{s'}\right) - (1-\sigma_s)\log(P_n^s) \\ &= (1-\sigma_s)\log(t_{ni}) + \lambda_n^s + \zeta_i^{s'} \end{aligned} \tag{36}$$

This gravity equation is very similar to that proposed by Anderson (1979) and Anderson and Van Wincoop (2003) to model gravity for demand of consumers with CES preferences, except that I estimate sector-specific CES production elasticities σ_s. Again, I identify σ_s using cross-sectional variation in bilateral trade costs t_{ni} and assume that $t_{ni} = d_{ni}^{\rho} \Pi_l \left(g_{l,ni}^{d_l}\right) \eta_{ni}^{ss'}$, where d_{ni} is distance, ρ is the distance elasticity of trade costs, and $g_{l,ni}$ are other gravity variables. The final estimating equation is:

$$\log\left(E_{ni}^{ss'}\right) = (1-\sigma_s)\rho\log(d_{ni}) + \sum_l \left[(1-\sigma_s) d_l G_{l,ni}\right] + \lambda_n^s + \zeta_i^{s'} + \varepsilon_{ni}^{ss'} \tag{37}$$

Again, I obtain bilateral distance between country pairs (d_{ni}) from CEPII. The other elements of $G_{l,ni}$ are indicators for common language and a shared border, also from CEPII. I estimate this equation separately for the 35 industries s. For estimation, I apply an ordinary least squares (OLS) estimator with origin (country-sector) and destination (country-sector) fixed-effects. This has been shown to be consistent (e.g. Head and Mayer, 2014). I again assume that $\rho = 0.177$. To account for other factors that could affect "multilateral resistance", I include fixed-effect for origins (λ_n^s) and destinations ($\zeta_i^{s'}$), as is common practice. Estimates are then consistent with alternative gravity set-ups that result in multiplicative bilateral resistance terms.

C. WIOD Country Overview

Table 5: The 40 countries included in WIOD

Country	**Population** (mio)	**Avg. Consumption** (k$)	**CO2 Intensity** (kg per $ output)
AUS	20.4	31.3	0.27
AUT	8.3	32.3	0.1
BEL	10.7	29.8	0.14
BGR	7.9	3.2	0.9
BRA	187.8	3.2	0.2
CAN	32.3	27.9	0.25
CHN	1313	1.4	0.79
CYP	0.7	23.5	0.27
CZE	10.4	10.2	0.4
DEU	82.9	28.9	0.14
DNK	5.5	38.4	0.17
ESP	43.8	24.2	0.14
EST	1.4	8.6	0.61
FIN	5.3	30.9	0.18
FRA	63.5	30.6	0.08
GBR	60.7	35	0.12
GRC	11.1	22.3	0.25
HUN	10.3	9.7	0.23
IDN	227.9	1.1	0.58
IND	1148.3	0.6	0.76
IRL	4.2	34.5	0.08
ITA	59	27.7	0.12
JPN	127.9	34.6	0.12
KOR	47.9	13.5	0.3
LTU	3.5	6.7	0.31
LUX	0.5	57.9	0.04
LVA	2.3	6.6	0.26
MEX	109.3	6.9	0.26
MLT	0.4	14.6	0.21
NLD	16.5	31.9	0.15
POL	38.9	6.3	0.56
PRT	10.5	17.7	0.18
ROM	21.8	3.6	0.65
RUS	147.8	3.2	1.41
SVK	5.6	7.4	0.4
SVN	2	15.9	0.19
SWE	9.1	33.6	0.08
TUR	67.5	5.8	0.27
TWN	23.2	13.4	0.38
USA	296.8	42	0.22

Notes: The 40 countries used in the main sample. Data from WIOD in 2004.

D. Parameter Estimates

Table 6: Average estimates of income semi-elasticity of demand by country

Country	$\bar{\hat{\beta}}$	**Country**	$\bar{\hat{\beta}}$
AUS	0.017	IRL	0.000
AUT	0.002	ITA	0.009
BEL	-0.019	JPN	0.039
BGR	-0.006	KOR	0.007
BRA	-0.016	LTU	0.000
CAN	-0.007	LUX	-0.011
CHN	-0.005	LVA	0.000
CYP	0.013	MEX	-0.019
CZE	-0.006	MLT	0.004
DEU	-0.003	NLD	-0.007
DNK	0.002	POL	-0.003
ESP	0.003	PRT	-0.004
EST	0.001	ROM	-0.004
FIN	0.008	RUS	-0.005
FRA	-0.004	SVK	-0.003
GBR	0.014	SVN	-0.002
GRC	0.013	SWE	0.002
HUN	0.001	TUR	-0.001
IDN	-0.026	TWN	0.016
IND	-0.031	USA	0.097

Notes: Average estimates of the income (semi)-elasticities as estimated from (8) and (9) for the WIOD cross-section 2004. Country averages across the 35 supply sectors each.

Table 7: Average estimates of demand and supply elasticities by sector

	WIOD Sector	$\hat{\bar{\beta}}$	$\hat{\bar{\gamma}}$	$\hat{\sigma}_s$
1	Agriculture, Hunting, Forestry and Fishing	-0.022	0.007	4.589
2	Mining and Quarrying	0.000	0.001	4.967
3	Food, Beverages and Tobacco	-0.016	0.015	4.353
4	Textiles and Textile Products	-0.004	0.002	4.726
5	Leather, Leather and Footwear	-0.001	0.001	5.394
6	Wood and Products of Wood and Cork	0.000	0.000	4.937
7	Pulp, Paper, Paper , Printing and Publishing	0.002	0.002	4.601
8	Coke, Refined Petroleum and Nuclear Fuel	0.000	0.003	5.203
9	Chemicals and Chemical Products	-0.001	0.003	4.479
10	Rubber and Plastics	0.000	0.001	4.694
11	Other Non-Metallic Mineral	0.000	0.001	4.725
12	Basic Metals and Fabricated Metal	0.000	0.002	4.429
13	Machinery, Nec	-0.005	0.005	4.539
14	Electrical and Optical Equipment	-0.004	0.005	4.420
15	Transport Equipment	-0.003	0.006	4.482
16	Manufacturing, Nec; Recycling	0.001	0.002	4.676
17	Electricity, Gas and Water Supply	0.000	0.006	4.779
18	Construction	-0.014	0.041	4.107
19	Sale, Mntnce and Repair Motor Veh.; Retail Sale of Fuel	0.003	0.004	4.821
20	Wholesale Trade and Commission Trade, Except of Motor Veh.	0.001	0.015	4.333
21	Retail Trade, Except of Motor Veh.; Repair of Household Goods	0.001	0.017	4.523
22	Hotels and Restaurants	0.006	0.014	4.697
23	Inland Transport	-0.008	0.006	4.579
24	Water Transport	-0.001	0.000	5.374
25	Air Transport	0.000	0.001	5.148
26	Other Supporting and Aux. Transport Activities; Travel Agencies	0.002	0.002	4.779
27	Post and Telecommunications	0.000	0.006	4.792
28	Financial Intermediation	0.006	0.013	4.845
29	Real Estate Activities	0.015	0.031	4.900
30	Renting of M& Eq and Other Business Activities	0.003	0.008	4.323
31	Public Admin and Defence; Compulsory Social Security	0.007	0.040	4.387
32	Education	0.004	0.015	4.875
33	Health and Social Work	0.022	0.026	4.593
34	Other Community, Social and Personal Services	0.004	0.016	4.467
35	Private Households with Employed Persons	0.001	0.001	5.657

Notes: Average estimates of the income (semi)-elasticities and price elasticities as estimated from (8) and (9) for the WIOD cross-section 2004. Sector averages across the 40 origin countries each. Third column are CES production elasticities estimated from (10).

Table 8: Consistency of parameter estimates - $\hat{\beta}$

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
2000	1.00	0.97	0.98	0.96	0.92	0.89	0.82	0.69	0.58	0.66
2001	0.97	1.00	0.96	0.94	0.92	0.88	0.81	0.69	0.58	0.64
2002	0.98	0.96	1.00	0.99	0.96	0.93	0.88	0.77	0.67	0.73
2003	0.96	0.94	0.99	1.00	0.99	0.97	0.93	0.84	0.75	0.80
2004	0.92	0.92	0.96	0.99	1.00	0.99	0.97	0.90	0.82	0.85
2005	0.89	0.88	0.93	0.97	0.99	1.00	0.99	0.93	0.86	0.89
2006	0.82	0.81	0.88	0.93	0.97	0.99	1.00	0.97	0.92	0.93
2007	0.69	0.69	0.77	0.84	0.90	0.93	0.97	1.00	0.98	0.97
2008	0.58	0.58	0.67	0.75	0.82	0.86	0.92	0.98	1.00	0.97
2009	0.66	0.64	0.73	0.80	0.85	0.89	0.93	0.97	0.97	1.00

Notes: Pairwise correlation, 1400 income elasticities estimated from (8) and (9), WIOD cross-sections.

Table 9: Consistency of parameter estimates - $\hat{\gamma}$

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
2000	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
2001	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
2002	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00
2003	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2005	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2006	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2007	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2008	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2009	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Pairwise correlations, 35 price elasticity parameters estimated from (8), WIOD cross-sections.

Table 10: Consistency of parameter estimates - $\hat{\sigma}$

	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
2000	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2001	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2002	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2003	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
2005	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2006	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	0.99
2007	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
2008	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00
2009	0.98	0.98	0.98	0.99	0.99	1.00	0.99	1.00	1.00	1.00

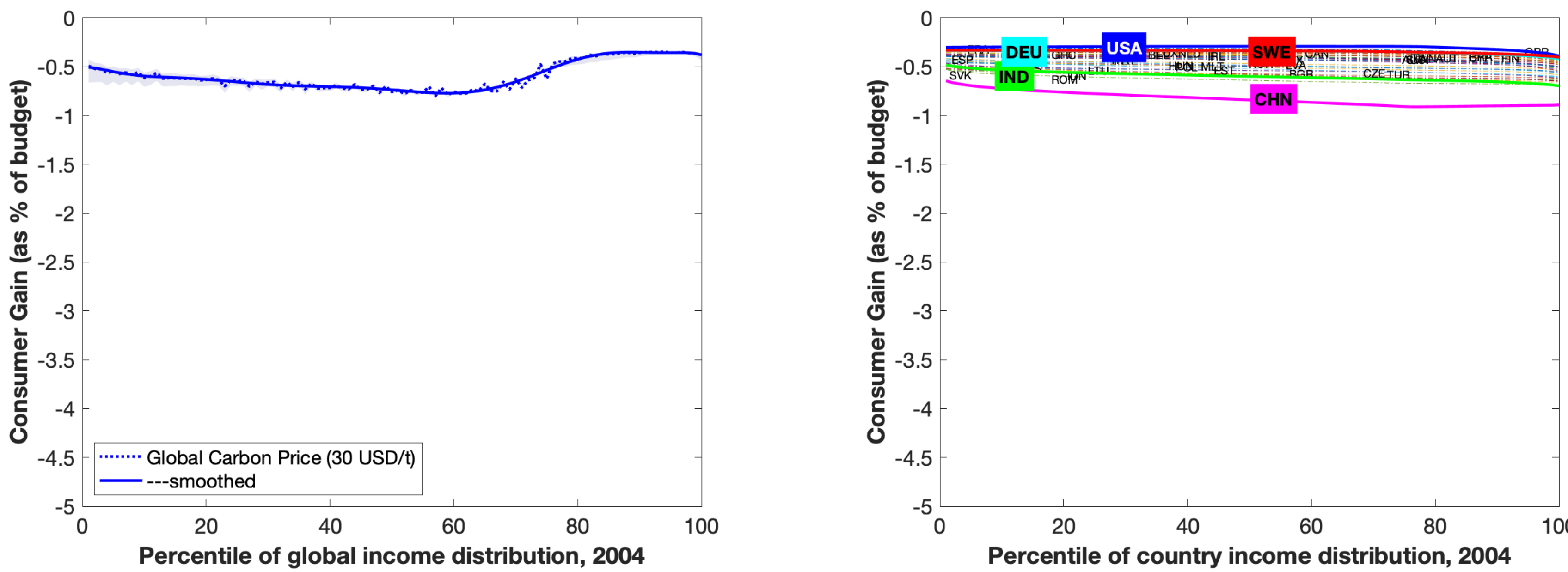
Notes: Pairwise correlations, 35 CES elasticities estimated from (10), WIOD cross-sections.

E. Additional results

Figure 7: Global price of 30 USD/t - All countries have Swedish emissions intensities]

(a) Global distribution

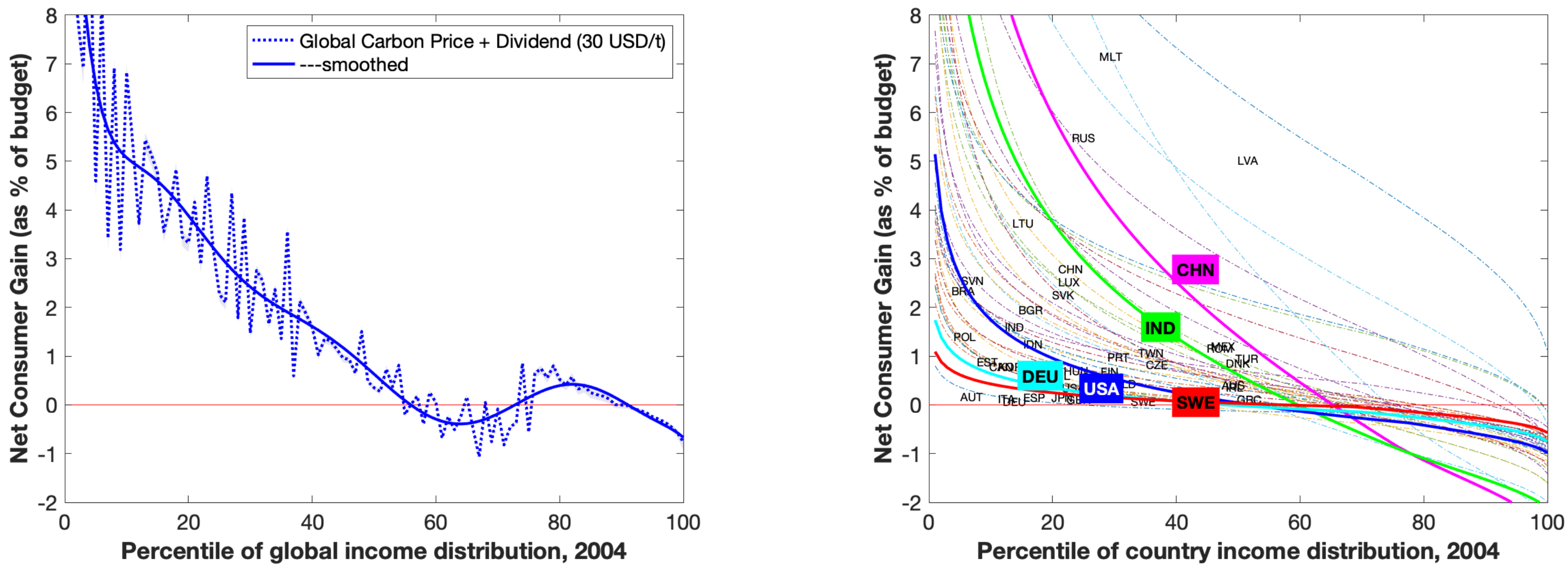
(b) Within-country distribution



Notes: Consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004 (40 WIOD countries), but assigning the emissions intensities of the Swedish sectors (d_{is}) to other countries worldwide. The horizontal axis shows percentiles of the income/expenditure distribution, both globally (Panel a) and within each of the 40 WIOD countries (Panel b) in 2004. Otherwise equivalent to Figure 1 and Figure 2.

Figure 8: Global price of 30 USD/t and national carbon dividend [source-side tax] - Consumer cost

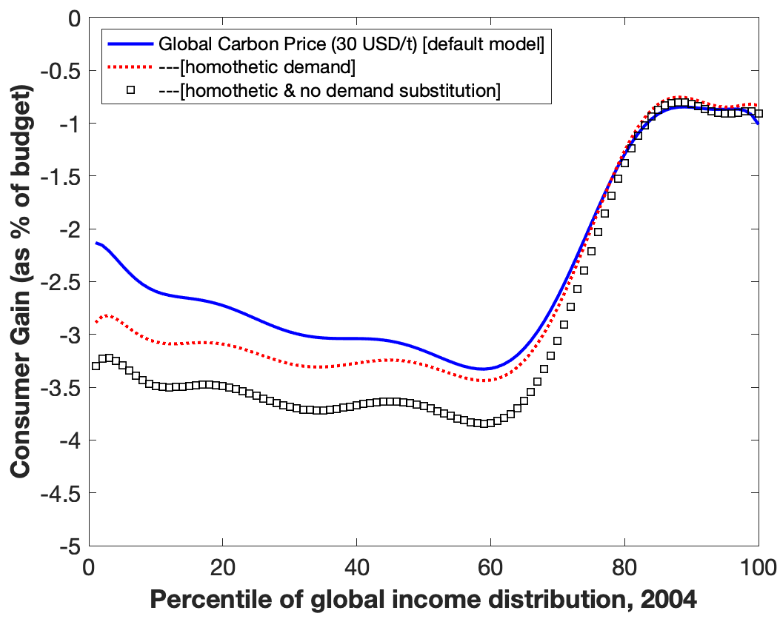
(a) Global distribution **(b)** Within-country distribution



Notes: Consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries), net of the benefits from a per capita carbon dividend in each country. Equivalent to Figures 3, except that here revenue is collected and redistributed in the country where emissions occur in production. The horizontal axis shows percentiles of the income/expenditure distribution, both globally (Panel a) and within each of the 40 WIOD countries (Panel b) in 2004.

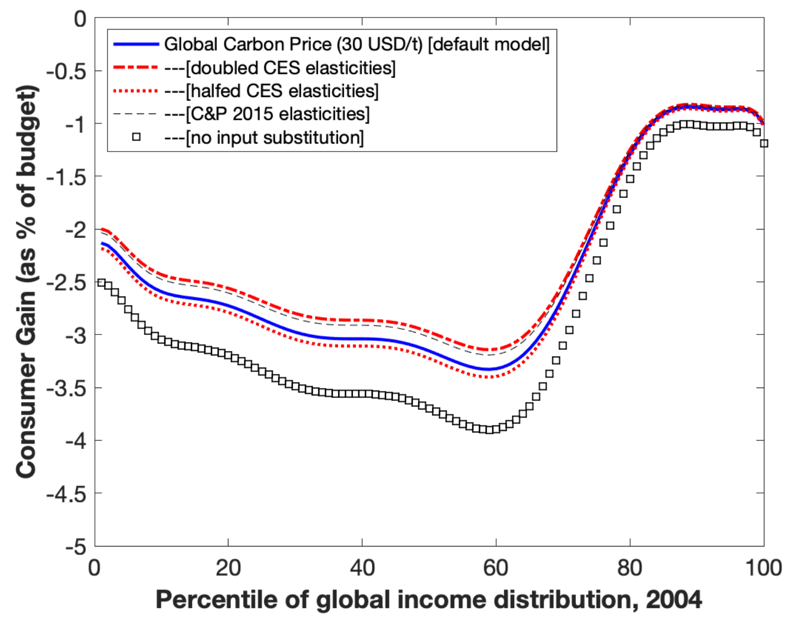
Figure 9: Sensitivity of main results to parameter estimates

(a) Demand: Income and substitution elasticities



Notes: Comparison of simulation results under different assumptions regarding income and substitution elasticities on the demand side. All show smoothed versions of the consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004. The solid blue line replicates the baseline results in Figure 1. The dotted red line shows the same estimates assuming homothetic demand within countries, setting all $\beta_i^s = 0$. The black squares in addition switch off demand substitution, $\gamma^s = 0$. It is thus based entirely on country-average expenditure shares observed in the data. The horizontal axis shows percentiles of the income/expenditure distribution across the 4.2 billion inhabitants of the 40 WIOD countries in 2004. The consumer gain is the welfare effect equivalent to a share change the total expenditure budget.

(b) Supply: Substitution elasticities



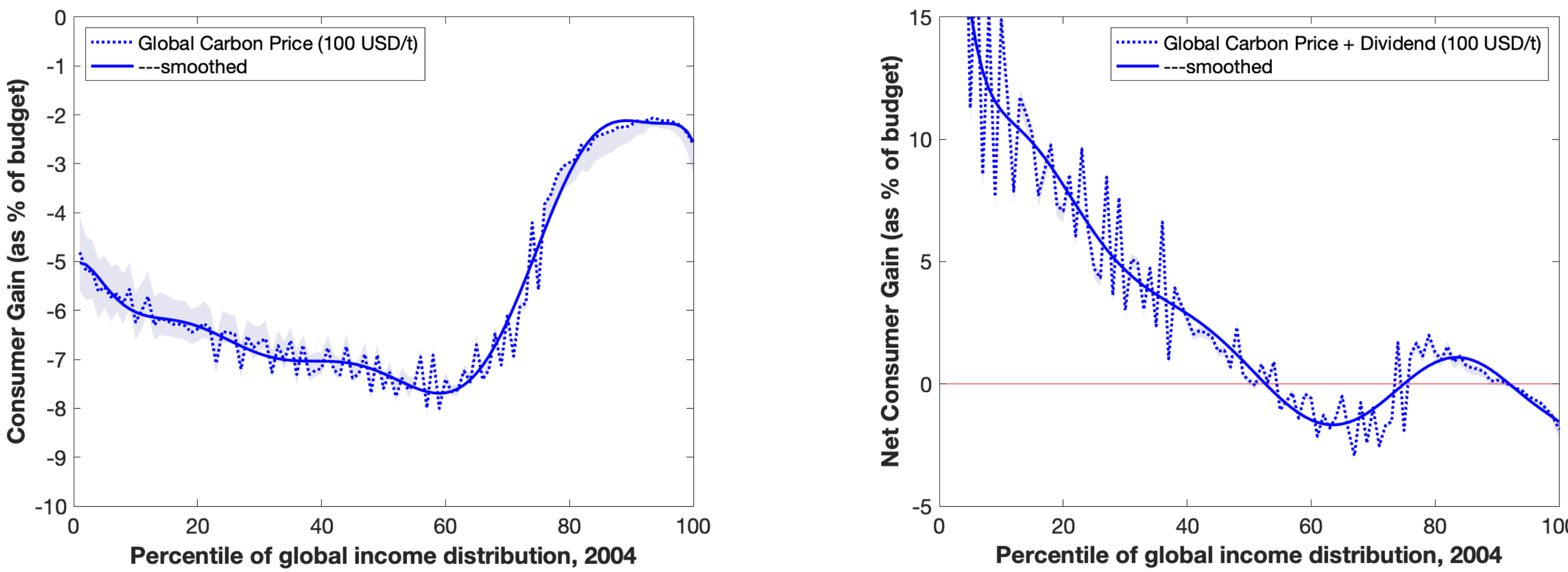
Notes: Comparison of simulation results under different assumptions regarding substitution elasticities in production. All show smoothed versions of the consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO_2 simulated at the end of 2004. The solid blue line replicates the baseline results in Figure 1. The dashed red line shows the same estimates when doubling the estimated CES production elasticities σ_s. The dotted red line instead uses halved elasticities. The dashed black line uses elasticities for traded sectors estimated by Caliendo and Parro (2015), Table 1. The black squares switch off input substitution entirely, maintaining original value chain structures observed in the data. The horizontal axis shows percentiles of the income/expenditure distribution across the 4.2 billion inhabitants of the 40 WIOD countries in 2004. The consumer gain is the welfare effect equivalent to a share change the total expenditure budget.

F. Alternative carbon price of 100 USD/t in 2004

Figure 10: Global price of 100 USD/t - Consumer cost

(a) Global price

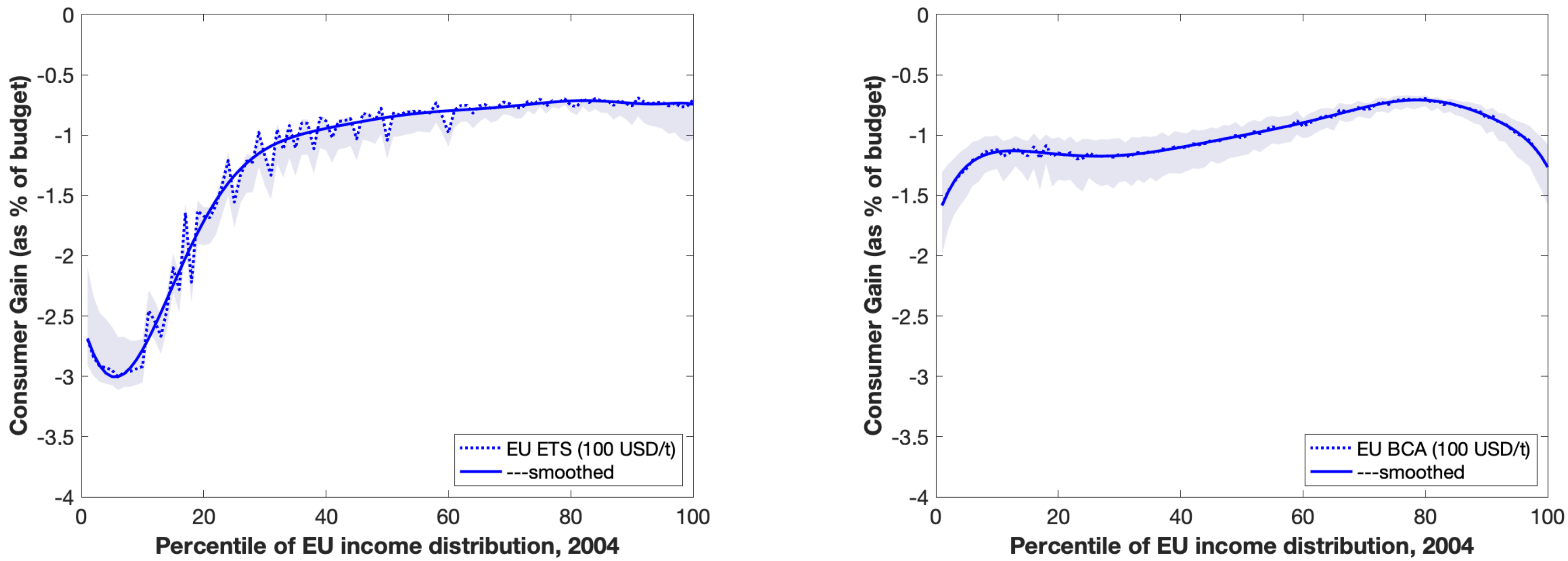
(b) Global price + dividends



Notes: Consumer welfare effect under a global uniform carbon price of 100 USD per ton of CO_2 simulated in 2004 (40 WIOD countries), standalone (Panel a) and net of the benefits from a per capita carbon dividend in each country (Panel b). The horizontal axis shows percentiles of the global income/expenditure distribution across the 40 WIOD countries. Otherwise equivalent to Figure 1 and Figure 3 (Panel a).

Figure 11: EU ETS and BCA of 100 USD/t - Consumer cost

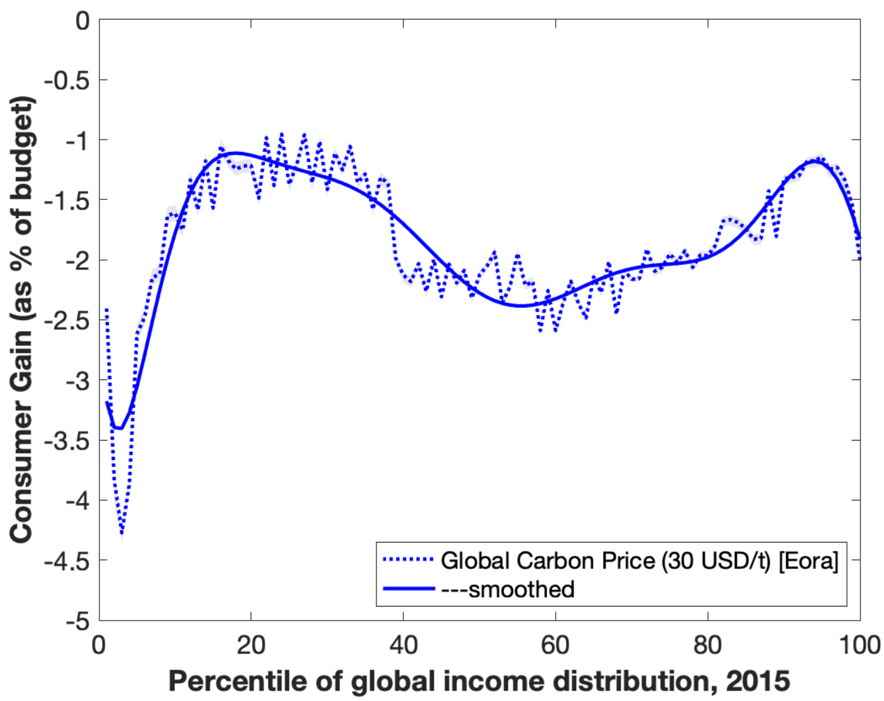
(a) EU Emission Trading Scheme **(b)** EU Border Carbon Adjustment



Notes: Consumer welfare effect under two EU carbon pricing scenarios: An EU-wide (27 countries) uniform carbon price of 100 USD per ton of CO_2, applied to the EU ETS target sectors and simulated in 2004 (Panel a) and a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to all sectors and simulated in 2004 (Panel b). The horizontal axis shows percentiles of the global income/expenditure distribution across the 40 WIOD countries. Otherwise equivalent to Panels (a) of Figures 4 and 5 respectively.

G. Carbon price in 189 countries (Eora) - 2015

Figure 12: Global price of 30 USD/t - Global distribution of consumer cost (Eora)



Notes: This figure shows the global distribution of the consumer welfare effect under a global uniform price of 30 USD per ton of greenhouse gas emissions (CO_2e) simulated in 2015 (189 Eora countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 7.2 billion inhabitants of the 189 Eora countries in 2015. The price is applied to all 189 Eora countries and all greenhouse gases (Kyoto classification) emitted from a large range of activities (including land use). The consumer gain is equivalent to a share change in total expenditure budget (dashed) and approximated with a 10th degree polynomial (solid). Shaded regions are 95% confidence intervals from 500 separate simulations, each using a different set of model parameters drawn from the joint normal distributions for parameter estimates from estimations (8), (9) and (10).