The Global Consumer Incidence of Carbon Pricing: Evidence from Trade

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Carbon pricing is often seen as regressive, disproportionately burdening low-income consumers. I show that higher prices following a carbon tax would be mildly regressive in industrialized countries, mildly progressive in developing countries, and steeply regressive across countries. Refunding revenues with national carbon dividends would reverse all three findings. Carbon taxes plus dividends would be globally progressive, even without international transfers. My approach to estimating the consumer incidence 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, Q52, Q56, Q58.

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1. Introduction

Governments around the world are introducing prices on carbon dioxide (CO\textsubscript{2}) emissions. In 2005, when the European Union launched its Emissions Trading Scheme (ETS), less than 5% of global greenhouse gas emissions were subject to a price. In 2019, price coverage exceeded 15% and is expected to surpass 20% when China launches its permit scheme (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 estimate the global distribution of that cost to consumers and show that it is globally regressive—it disproportionally affects poorer consumers—and more so between than within countries.

My approach has two key advantages. First, it captures distributional effects across consumers worldwide and the propagation of carbon prices through global value chains. I exploit this advantage to estimate for the first time how the consumer cost of carbon pricing is distributed globally—both between many countries and at different 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 costs. Within countries, consumption baskets vary with income and so do consumer costs. Since truly multilateral climate policy was often deemed unlikely (e.g. Poterba, 1993), the literature has largely focused on the within-country effects of unilateral climate policy. But even domestic climate policy can have distributive effects across countries since goods are traded internationally and produced in globally connected value chains. The emergence carbon pricing schemes around the world, and the potential for global coordination as envisioned by the Paris Agreement signed in 2015, warrant a global approach to welfare analysis.

The second advantage of my approach is that it allows for carbon prices that are differentiated both by origin and destination of goods, a feature that I use to estimate the distributional effects of unilateral climate policy, specifically the EU ETS, and environmental trade policy, specifically an EU Border Carbon Adjustment (BCA) mechanism.

These advantages come with a cost. Mine is a partial equilibrium framework. It allows for consumer substitution, value chain adjustments and fuel shifting. But it ignores other, potentially important general equilibrium effects of carbon pric-
ing. 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 is such a strong assumption, I test it directly against consumer survey data from multiple countries.

Conceptually, this paper focuses on ‘use side’ effects—the cost to consumers from higher prices. As such, it complements research on other channels that shape the global welfare effects of climate policy. Importantly, we may wish to compare the cost of carbon pricing to the benefits of reduced climate damage. Recent evidence suggests that these benefits vary significantly across regions and may fall disproportionately to poor countries with high average temperatures (Burke et al., 2015; Nordhaus, 2017). By estimating how the consumer cost of carbon pricing is distributed globally, I contribute another element towards a more complete welfare analysis. These results can shed light on who may be prone to resisting climate policy and help inform the design of more equitable policy.

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

On the supply side, I model substitution of intermediate inputs along global value chains, again using gravity equations to identify the relevant model parameters. A carbon price translates into changes in the structure of global production as emissions-intensive inputs become more expensive. I also allow producers to substitute between primary fossil fuels used in production. Still, my approach is static other aspects, abstracting from the consequences of carbon pricing for factor incomes (Fullerton and Heutel, 2007; Rausch et al., 2011) and energy-saving technological innovation (Acemoglu et al., 2012a; Aghion et al., 2016). Nevertheless, the supply side adjustments that I do capture significantly mediate the cost increase
to consumers and render my estimates more realistic. A naive extrapolation based on the emissions content of consumption, while ignoring supply side adjustments, significantly over-estimates the consumer cost.

I investigate three scenarios. The first is a global uniform carbon price as prescribed by economic theory on efficiency grounds. I show that the consumer cost in absence of revenue recycling would be highly regressive at the global scale. Consumers in the bottom half of the world income distribution suffer an equivalent variation welfare loss more than twice as large as that of consumers in the top 10%. Importantly, I find that differences between countries dominate those within them. Carbon pricing affects average consumers in poor countries more than poor consumers in average countries. These differences between countries are mostly due to the fossil-fuel-intensity of production rather than differences in the composition of aggregate consumption.

We know that the distributional effect of any tax, at least within countries, ultimately depends on how the collected revenue is used (Metcalf, 2009; Gonzalez, 2012). I show that this also holds at the global level, after allowing national governments to redistribute carbon pricing revenues as per capita lump sum transfers. Such ‘carbon dividends’ feature in many carbon pricing proposals, including that proposed by the Climate Leadership Council for the United States. Carbon dividends render the global uniform carbon price progressive—disproportionately benefiting low income consumers—both within countries and even globally. No transfers between countries are needed to obtain this result.

A global uniform carbon price may not be likely anytime soon. I thus investigate two further scenarios that are more acutely policy relevant. As a second scenario, I assess the introduction of the EU ETS in 2005. Similar to the global carbon price, the EU ETS is likely 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 the consumer cost from Border Carbon Adjustments (BCA), which are discussed as policy instruments to counter competitive pressures and carbon leakage under unilateral climate policy (see e.g. Fowlie et al., 2016). I find that complementing an EU-wide carbon price with BCA would generate a rather small ‘use side’ cost, which follows an inverted U-shape. This time, there is less variation between EU member states.

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1The Climate Leadership Council’s plan is available at https://www.clcouncil.org/.
This article contributes to three distinct literatures. First, it contributes to the literature on the distributional effects of environmental and energy taxes. Much of this literature is focused on the within-country incidence of domestic policies. Results suggest that the consumer cost of pricing carbon emissions (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, these estimates vary with modelling choices and differ by country. In particular, energy taxes appear much less regressive, and sometimes neutral, when measures of permanent income are used (Fullerton, 2011) and when demand responses by consumers are taken into account (West and Williams, 2004). In addition, general equilibrium effects may be important. Rausch et al. (2011) find that changes in factor incomes, for example to land and capital, may alter the incidence of a carbon tax. Sterner (2012) summarizes the literature on the within-country incidence of taxing transport fuels and highlights that, while such policies appear regressive in some countries, they may well be progressive in others.

There are fewer contributions that explicitly estimate how the average consumer cost of carbon pricing differs between countries (early examples are Whalley and Wigle, 1991; Shah and Larsen, 1992), though such differences are often acknowledged in climate policy negotiations (e.g. Mehling et al., 2018). This article contributes to the literature by estimating the global consumer cost incidence of carbon pricing—both between and within many countries. In line with the literature on within-country incidence, I estimate that carbon pricing is regressive in some, mostly rich countries and progressive in some poorer ones. But I also find that differences between countries are much more important in shaping the global incidence. Finally, I find that the progressive nature of ‘carbon dividends’ which has been documented at the country level also hold at the global scale.

Second, this article contributes to the literature on the design of EU climate policy. There is a large literature studying the design and effectiveness of the EU ETS introduced in 2005. The literature includes both ex ante and ex post evaluations (see surveys by Ellerman and Buchner, 2007; Martin et al., 2016). This article contributes to the literature by providing ex ante estimates of the EU ETS’s consumer incidence across all 490 million EU residents. Further, it contributes to the literature on carbon pricing targeted at traded goods. BCA can level the playing field by pricing the emissions content of imports that do not face a carbon price at
home (Markusen, 1975; Hoel, 1996). There is a growing literature on the effectiveness of BCA in countering leakage (Böhringer et al., 2012; Fowlie et al., 2016) and their burden to different countries (Böhringer et al., 2018). Despite their theoretical appeal, there is to date scarce evidence on how the consumer cost of BCA is distributed within countries. My model distinguishes between the demand for domestic goods and import goods from different origins. It is thus uniquely suited to estimate how the cost of BCA is distributed across consumers, which I do for the EU setting.

Third, this article adds to a growing literature applying structural gravity approaches to environmental policy analysis. For example, Shapiro (2016) uses such an approach to characterise the CO₂ content of international shipping. Larch and Wanner (2017) simulate the trade and aggregate welfare effects of carbon tariffs. And Caron and Fally (2018) use a gravity approach to demonstrate the role of country-level income in shaping the CO₂-content of aggregate consumption. Here, I demonstrate that the structural gravity approach can be useful in answering a different question—by estimating how the consumer cost of carbon pricing is distributed globally. The structural gravity approach adopted in this and other papers represents a middle-ground between general equilibrium models and partial equilibrium approaches using detailed micro-data. General equilibrium analyses can capture a large number of adjustment margins and complex interactions, but often focus on a single representative consumer. In contrast, my framework allows for greater heterogeneity of consumers—both between and within countries. Another approach to incidence analysis relies on detailed micro-data from consumption surveys, but usually focuses on single countries. In contrast, my approach captures the consumer cost at a global scale within a unified framework. My framework can in principle be applied to any set of exogenous price changes. It is best suited for analyses at the global scale that involve international trade and make use of environmentally extended multi-regional input-output (MRIO) data.
I estimate within a unified framework 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 dynamic model of global value chains and emissions accounting methods using input-output tables.

My model is not a complete general equilibrium model. Instead, it is intended to capture—while remaining tractable—those adjustment 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 substitute away from carbon-intensive energy fuels in their own production, as well as dirty intermediate inputs. This results in a re-calibration of global value chains, which spurs softened, and arguably more realistic, price increases experienced by consumers. In this section, I give an overview of the model. In the next section, I explain how I estimate model parameters from bilateral trade flows. The Appendix provides further detail.

2. Modeling the global cost of carbon pricing

The core of my analysis is a standard Almost Ideal Demand System (AIDS) expanded to many countries. Key to capturing distributional effects, AIDS incorporates non-homothetic preferences—consumers at different income levels within countries differ in their demand for emissions-intensive goods. The model can be summarized using the expenditure share that consumer \( h \) with budget \( x_h \) devotes to good \( j \):

\[
s_{jh}(p, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{k=1}^{J} \gamma_{jk} \log p_k + \beta_j \log \left( \frac{x_h}{a(p)} \right)
\]  

(1)

Expenditure shares depend on preferences for good \( j \) (\( \alpha_j \)), prices of all goods \( k \) (\( p_k \)) and the consumer’s real income (\( \frac{x_h}{a(p)} \)). Cross-price elasticities between goods \( j \) and \( k \) (\( \gamma_{jk} \)) shape the degree of demand substitution. Non-homothetic consumption is defined by income (semi)-elasticities for goods \( j \) (\( \beta_j \)), which ultimately drive differential effects across income groups. Here, positive values (\( \beta_j > 0 \)) mean 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 to estimate model parameters from bilateral trade flows.
flows between countries and sectors. Here, I follow closely the methodology proposed by Fajgelbaum and Khandelwal (2016), who estimate how the gains from trade are distributed across consumers. I adopt this non-homothetic gravity framework to estimate the global distributional effects of carbon pricing. The approach pairs AIDS with the assumption of national product differentiation (Armington, 1969). Each sector $s$ from country $i$ sells a different variety, so that $J = S \times I$. Consumers’ average preferences for goods ($\alpha_j$) differ by destination country, but consumers in all countries share the same price and income elasticities ($\gamma_{jk}$ and $\beta_j$). The latter is a strong assumption, 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 $j$, $\hat{p}_j = d\log(p_j)$, experienced by consumer $h$ is:

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

$$= \hat{W} + \hat{\psi}_h + 0 \quad (2)$$

**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 a country, $\hat{W}$, and an individual cost to each consumer $h$, $\hat{\psi}_h$. The latter is a function of $h$’s income ($x_h$) relative to the country’s inequality-adjusted mean income ($\tilde{x}$)\(^2\). It represents deviations from average expenditure shares driven by income elasticities $\beta_j$. In sum, $\hat{W}$ captures the average consumer incidence between countries while $\hat{\psi}_h$ captures distributional effects within countries\(^3\). The final element is the change in (log) nominal income $\hat{x}_h$. Other than a carbon dividend to recycle carbon pricing revenue, I assume that incomes are unaffected by climate policy ($\hat{x}_h = 0$)\(^4\).

\(^2\) $\tilde{x} = \bar{x} e^\Sigma$ where $\Sigma = E \left[ \frac{y}{x} \log \left( \frac{y}{x} \right) \right]$ is the Theil index of income inequality.

\(^3\) In simulations with non-marginal changes in prices $\hat{p}$, equation (2) is integrated numerically to account for demand substitution in 5 intermediate steps between initial and adjusted expenditure.

\(^4\) The incidence of environmental policy may be altered when considering changes to factor incomes, especially wages (Fullerton and Heutel, 2007, 2010; Rausch et al., 2011). While this is an important consideration, I focus on the global “use side” effects due to higher prices.
2.2. Supply: Input substitution in global value chains

Producers also experience changes in input costs and may react 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. It is thus important to capture such supply-side adjustments when estimating the welfare effect on consumers worldwide. To do so, I employ a simple model of global value chains, which allows for intermediate input substitution and at the same time tracks emissions throughout value chains.

To isolate the effect of input substitution on carbon emissions, I assume that production requires only energy and a composite of intermediates, in fixed proportions\(^5\). Specifically, I assume that producers in the perfectly competitive sector \(j\) have identical Constant Elasticity of Substitution (CES) production functions across \(K\) intermediate inputs with prices \(\phi_{kj}\). All sectors provide intermediates and final goods, \(J = K\). For any level of output \(X_j\) in sector \(j\), the representative producer minimizes input costs \(C_j\), resulting in the following expenditure shares on intermediate inputs \(k\):

\[
S_{kj} = \frac{\phi_{kj} f_{kj}}{C_j} = a_{kj} \phi_{kj}^{(1-\sigma_j)} P_j^{\sigma_j - 1} \tag{3}
\]

The expenditure share of input \(k\) is decreasing in its price \(\phi_{kj}\) relative to the input price index of sector \(j\), \(P_j = (\sum_k a_{kj} \phi_{kj}^{(1-\sigma_j)}\)^{1/(1-\sigma_j)}. Constant returns to scale combined with perfect competition imply that input shares and output prices are independent of the level of final demand. Prices are proportional to input cost, a property that I use in my counterfactual simulations.

In the next section, I discuss how I estimate the relevant substitution elasticities \(\sigma_j\) using a structural gravity approach, this time using data on bilateral inter-industry trade in intermediates. Once parameterized, I simulate input substitution in response to carbon pricing and approximate the new equilibrium in global input-output linkages—the structure of global value chains. The importance of accounting for the structure of production has previously been demonstrated by Caliendo and Parro (2015) when estimating the welfare effects of NAFTA tariff reductions.

To trace emissions, and their price effect, through value chains, I use input-output

\(^5\)This is equivalent to assuming that all other factors of production, and their prices, are proportional to the composite of intermediates.
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 \( C \) with elements \( c_{kj} \) which show the dollar amount of intermediate input from industry \( k \) necessary for the production of a dollar of output in industry \( j \). Following Leontief (1970), the Total Requirement matrix \( T \) is:

\[
\mathbf{x} = [\mathbf{I} - \mathbf{C}]^{-1} \mathbf{y} = \mathbf{Ty}
\]  

(4)

Matrix elements \( t_{kj} \) show the dollar amount of total input from sector \( k \) used to produce a dollar of final output in sector \( j \), accounting for all upstream processes. These can be translated into total emissions intensities:

\[
\mathbf{e} = \mathbf{T}' \mathbf{d}
\]  

(5)

The \( J \)-vector \( \mathbf{d} \) of direct emissions intensities \( \delta_j \) describes for each sector the \( \text{CO}_2 \) emissions per dollar of output in sector \( j \). Element \( \varepsilon_j \) of \( \mathbf{e} \) instead shows the total \( \text{CO}_2 \) emissions intensity (tons of \( \text{CO}_2 \) per $) of a dollar of final consumption from sector \( j \), including all upstream emissions in sectors \( k \). The effect of carbon pricing on the final price of good \( j \) is a function of \( \varepsilon_j \).

**Price dynamics:**

The total emission intensity \( \varepsilon_j \) of final good \( j \) determines its relative price increase\(^6\). Without input substitution, this is straightforward. Assume a carbon price \( \tau \) (in $ per ton of \( \text{CO}_2 \)) on all emissions. Holding constant production, this will raise final prices to a new level \( p_j^{\text{new}} = (1 + \tau \varepsilon_j) p_j \). This is the standard input-output based approach to emissions accounting which is static and uses the existing structure of value chains (following Leontief, 1970).

When allowing for input substitution and differentiated carbon prices, slightly more involved price dynamics are required. When producers adjust intermediate input use in response to carbon prices, this will alter the structure of value chains (\( C \)) and, consequently, emissions intensities (\( \varepsilon_j \)). This will invite yet further adjustments to inputs until we reach a new equilibrium:

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\(^6\)In this model, it does not matter if 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 \( \text{CO}_2 \) 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.
**Proposition 2 (Price effect with input substitution)** We levy carbon prices $\{\tau_{kj}\}$ on intermediates $k$ used in production $j$. Given initial input requirements $\{c_{kj}\}$ and direct emissions intensities $\{\delta_j\}$, the new equilibrium is defined jointly by:

$$c_{jk}^{\text{new}} = c_{jk} \left( \frac{\sum_i a_i (1+\tau_{ik} \epsilon_{ki}^{\text{new}}) \sqrt{\sum_k \delta_k^{\text{new}}}}{1+\tau_{jk} \epsilon_{kj}^{\text{new}}} \right) \sigma_k \forall k, j \quad (6)$$

$$\epsilon^{\text{new}} = \left[ (I - C^{\text{new}})^{-1} \right]' \mathbf{d} \quad (7)$$

**Proof.** See Appendix A.2. ■

For each carbon pricing scenario, I approximate numerically the new equilibrium value chain ($C^{\text{new}}$), emission intensities ($\epsilon_{kj}^{\text{new}}$) and prices ($p_{kj}^{\text{new}}$). 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. The key assumption is that the total amount of energy content (TJ) needed to produce one unit of output in each sector remains unchanged, but producers can shift between the fuel source of that energy. To model these adjustments, I rely on meta-survey estimates of pairwise interfuel substitution by Stern (2012), paired with data on CO$_2$ emissions by country-sector split and fuel type. In the data I use, described in the next Section, emissions are assigned to that sector where a particular fuel is combusted (Genty et al., 2012), rather than to the mining and petroleum sector supplying it. This allows me to simulate fuel switching first, generating new direct emission intensities $\delta_j^{\text{new}}$, which then feed into the intermediate input substitution process that generates $C^{\text{new}}$ and $\epsilon_{kj}^{\text{new}}$. 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 ($\delta_j^{\text{new}}$) of the electricity sector in turn lowers the total value chain emissions of all downstream sectors ($\epsilon_{kj}^{\text{new}}$).

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$^7$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).

$^8$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.

$^9$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).
**Discussion and Limitations:**

The primary purpose of my framework is to capture distributional effects across consumers in many countries and at different income levels. It further accounts for some important adjustment margins. In particular, the supply-side adjustments—fuel switching and intermediate input substitution—significantly mitigate the price increase passed on to consumers and render the incidence estimates more realistic.

Nevertheless, I exclude other margins of adjustment that may be important. I assume perfect competition and thus cannot model the possibility of strategic price adjustments in the market for fossil fuels. I also assume perfect pass-through of carbon prices onto consumers. Prices are at all times proportional to input costs. Any imperfect pass-through of carbon prices, for which there is indeed evidence at least in some industries (Ganapati et al., 2019), could be approximated in my framework by an appropriately smaller carbon price. 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 degree of substitutability between fuels. This excludes 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 the repercussions of carbon pricing for transport margins (Shapiro, 2016) and of induced fluctuations in exchange rates, which may be substantial under border tax adjustments (Barbiero et al., 2019). Each of these omissions may bias my estimates as long as their effect differs across countries and income groups.

Finally, my analysis is limited conceptually to estimating the distributional effects of carbon pricing on the ‘use side’—the consumer cost due to higher final goods prices. I ignore various other dynamics that can be important for the welfare effects of carbon pricing, including changes to (factor) incomes (Rausch et al., 2011), the distribution of avoided climate damages, and the way in which the revenue collected from pricing carbon is used (West and Williams, 2004).
3. Calibrating the model

My model can be calibrated using environmentally enhanced Multi-Regional Input-Output (MRIO) databases. I primary rely on the World Input-Output Database (WIOD), which covers 35 sectors in 40 countries (plus ‘Rest of the World’), in yearly cross-sections between 1996 and 2009. WIOD Environmental satellite accounts contain CO$_2$ emissions and fuel use for each of those country-sectors ($\delta_j$). WIOD Input-Output tables contain the bilateral trade flows between country-sector pairs and value chain structure ($C$). While WIOD one of the most commonly used MRIO databases, 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.$^{11}$

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 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 cross-country differences in sectoral productivity and trade cost, and where goods are differentiated by origin. Essentially, each sector from each country sells a different variety. Consumers in destination country $n$ choose among goods from sectors $s$ and origins $i$. In WIOD, this translates into 1400 varieties ($J = S \times I = 35 \times 40$).

Trade costs between country-pairs ($t_{ni}$) are of the iceberg variety,$^{12}$ adding a constant multiple to prices $p_{ni}^s = t_{ni}p_i^s$. I estimate income semi-elasticities ($\beta_i^s$) for each of the 1400 varieties and price elasticities ($\gamma^s$) 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 described in Fajgelbaum and

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$^{10}$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.

$^{11}$The code for the model described in Section 2, to be made available alongside this article, can be calibrated using any MRIO database and alternative choices of elasticity parameters.

$^{12}$This proportionality of trade costs is maintained in counterfactual analyses under carbon pricing.
Khandelwal (2016), and elasticity estimates are very similar. A detailed description of the approach is in the Appendix B.1. I estimate the following equation for aggregate expenditure shares \( S_{ni}^s \) by consumers in country \( n \) on goods from sector \( s \) and country \( i \):

\[
S_{ni}^s = \frac{Y_i^s}{Y_W} + \alpha_i (S_{ni}^s - S_{W}^s) - (\gamma^s \delta^s)D_{ni} + \sum_l (\gamma^s \delta^s_l)G_{l,ni} + (\beta_i^s - \alpha_i \beta^s) \Omega_n + \varepsilon_{ni}^s \tag{8}
\]

Consumers in destination \( n \) buy more from sector \( s \) in origin \( i \) if that sector is large relative to the world economy \( \left( \frac{Y_i^s}{Y_W} \right) \) and if consumers in \( n \) spend more on goods in sector \( s \) relative to the world \( ((S_{ni}^s - S_{W}^s)) \). Variation in bilateral trade costs helps identify price elasticities \( (\gamma^s) \). 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 distance between country pairs, appropriately transformed \( (D_{ni}) \), as well as indicators for common language and a shared border \( (G_{l,ni}) \).

Variation in the inequality-adjusted mean income of destination \( n \) relative to the world \( (\Omega_n = y_n - \bar{y}_W) \)\(^{13}\) identifies income elasticities \( (\beta^s_i) \). If textiles from the United States are consumed more in richer and more unequal countries than textiles from India, then they must have a higher income elasticity. \( \Omega_n \) is calculated using country-level population and income (GDP) 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 \( a(p) \) with a Stone price index for each destination country \( n \) using quality-adjusted prices as provided by Feenstra and Romalis (2014).

Estimation of (8) yields estimates \( \hat{\alpha}_i, (\hat{\beta}_i^s - \hat{\alpha}_i \hat{\beta}^s) \), \( (\gamma^s \delta^s) \). To pin down price elasticity parameters \( \hat{\gamma} \), I follow Novy (2013) (and Fajgelbaum and Khandelwal, 2016) in setting \( \rho^s = \rho = 0.177 \) for all \( s \). A second estimation equation helps to identify the missing parameters \( \hat{\beta}^s \). I estimate an Engel curve projecting aggregate expenditure shares in country \( n \) for sectors \( s \) on the inequality-adjusted real income \( y_n \):

\[
S_{ni}^s = \alpha^s + \beta^s y_n + \varepsilon_{ni}^s \tag{9}
\]

\(^{13}\) Inequality-adjusted real income, \( y = \log \left( \frac{x}{\alpha(p)} \right) \), is price- and inequality-adjusted mean expenditure \( \bar{x} = \bar{x}\Sigma \), where \( \Sigma = E \left[ \frac{1}{p} \log \left( \frac{p}{y} \right) \right] \) is the Theil index of income inequality.
Estimates of $\hat{\beta}$ together with the estimates of $\hat{\alpha}$ from the above gravity estimation are sufficient to identify origin-sector specific income semi-elasticities $\hat{\beta}_i$.

### 3.2. Supply: Estimating production function parameters

On the supply side, I again estimate model parameters from trade flows—this time using data on bilateral inter-industry trade, which is provided separately in WIOD/Eora. I consider bilateral inter-industry trade 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 ($= (35 \times 40)^2$) such industry 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 goods from sector $s$ whether they are used as intermediates or final goods ($p_{ni} = \phi_{ni}$) and that intermediates are subject to iceberg trade costs $t_{ni}$ between destination $n$ and origin $i$, $p_{ni}' = t_{ni}p_{i}'$. Finally, I assume that the production functions are identical for each sector $s$ across countries $n$ ($\sigma_{n,s} = \sigma_s$ and $a_{ni}^{s,s'} = a_{i}^{s,s'}$, $\forall n$).

This approach is similar to the canonical CES gravity estimation following Anderson (1979) and Anderson and Van Wincoop (2003). Details are provided in Appendix B.2. I estimate the following equation for the share spent by sector $s$ in destination $n$ on intermediate inputs from sector $s'$ in origin $i$:

$$\log\left(S_{ni}^{s,s'}\right) = (1 - \sigma_s)\rho\log(D_{ni}) + \sum_{l} \left[(1 - \sigma_s)\delta_{l}\log G_{l,ni} + \lambda_{n}^{s} + \omega_{n}^{s'} + \epsilon_{ni}^{s,s'}\right] + \lambda_{n}^{s} + \omega_{n}^{s'} + \epsilon_{ni}^{s,s'} \quad (10)$$

Sector-specific CES production elasticities $\sigma_s$ 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. I estimate this equation separately for the 35 sectors $s^{14}$ 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$^{15}$.

---

$^{14}$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 $\rho = 0.177$.

$^{15}$Simulations show that allowing full substitution across input sectors further softens price increases, but does not overturn any of the qualitative findings reported below.
3.3. Model overview and parameter estimates

Table 1 gives an overview of the framework used here. The primary purpose is estimating 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 captured by the origin-sector specific income semi-elasticities ($\beta_s^i$), as well as consumer substitution across origins within sector through price elasticity parameters ($\gamma^s$). 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 ($\beta_s^i$) and 35 sector-specific price elasticity ($\gamma^s$) parameters.

On the supply side, CES production provides for substitution of intermediate inputs across origins within sector. Substitution across primary energy fuels used in production—coal, oil, gas and renewables—is based on the assumption of constant energy content (in TJ) per output. Gravity equation (10) yields estimates of the CES production elasticities ($\sigma_k$), of which there are again 35 in the case of WIOD. Elasticities of interfuel substitution come from a literature survey (Stern, 2012).

<table>
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<th>Table 1: Method overview</th>
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<td><strong>Theory</strong></td>
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**Notes:** Overview of the key model characteristics and data sources.

**Parameter robustness:** These estimates rely on a number of assumptions outlined above and further detailed in Appendix B. Since they are based on cross-sectional patterns of bilateral trade flows, it is plausible to assume that they represent long-term rather than short-term elasticities.

I provide a summary of estimated demand elasticities in Appendix C. 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. Hence, I show that results without either forms of substitution generate larger magnitudes of cost, but a very similar relative distribution.

My demand elasticities are nearly identical to those reported by Fajgelbaum and Khandelwal (2016) who also provide an extensive discussion of the limitations to this approach and underlying assumptions. Reassuringly, the estimates are highly consistent over time and correspond to intuition. For example, I consistently estimate agriculture to be a necessity ($\hat{\beta}_s < 0$) and real estate services to be 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 consumer incidence results to more traditional measures constructed using consumer survey data from multiple countries, finding a relatively good fit.

Beyond these ‘sanity checks’ of parameter estimates, I perform sensitivity analysis in two ways. First, I include confidence intervals from simulations using random parameter draws ($\hat{\beta}_i^x$, $\hat{\gamma}$) 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. All results reported below appear qualitatively robust.
4. The global consumer cost of carbon pricing

We now turn to estimates of the global consumer cost under three carbon pricing scenarios. First, I simulate a world where all countries implement a uniform carbon price. This is what economic theory may suggest based on efficiency grounds to meet 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 Scheme (ETS). Results look similar for later years. While a global uniform price may not be realistic anytime soon, an EU-wide carbon price already exists. My second scenario is the introduction of the EU ETS 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/t\textsuperscript{16}. 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 dashed line shows estimates for the average change in consumer welfare, expressed as a share of annual expenditure. Negative values represent welfare losses. The solid line shows a 10th degree polynomial approximation thereof. The blue band represents 95\% confidence intervals\textsuperscript{17}. 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 loosing between 2\% and 3\% of income—is more than twice as large as that of consumers in the top 20\%.

The second insight is that the incidence differs between countries. Figure 2 shows the cost distribution in each of the 40 countries, across percentiles of the country income distribution. 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

\textsuperscript{16}Some may argue that a carbon price of 30 USD/t of CO\textsubscript{2} is low compared to estimates of the climate externality. I show in Appendix F that, while the overall cost is higher, the relative incidence of a carbon price of 100 USD/t is similar to the results reported here for 30 USD/t.

\textsuperscript{17}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).
Figure 1: Global price of 30 USD/t - 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).

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).

But Figure 2 also suggests a third, more nuanced insight: The consumer incidence of carbon pricing varies much more strongly between countries than within them. Put differently, the slopes of the lines in Figure 2 is much less important than the distances between 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%) and 90th (4.0%) percentiles. Differences between countries matter more than those within them.
Figure 2: Global price of 30 USD/t - 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.

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

The incidence between countries shown in Figure 2 could be driven differences in the aggregate consumption (Caron and Fally, 2018) or 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 most important factor to explain the consumer cost difference between countries. The reason is home bias—Chinese consumers spend more of their budget on Chinese rather than, say, Swedish goods. The reverse is true for Swedes. Since value chains in China and Sweden have starkly different emissions intensities, this could explain why carbon pricing hurts Chinese consumers more than Swedish ones. To show that, Appendix Figure 8 replicates Figures 1 and 2, but assuming that each sector in each country had the same direct emissions intensity ($d_{it}$) as 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. 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. But carbon pricing may also generate revenues, which governments can use to offset that cost. In Figure 3 show how revenue recycling change the distributional effect of carbon pricing. I assume that governments redistribute 100% of the revenue in each country, splitting it equally among domestic consumers. Such ‘carbon dividends’ feature in many policy proposals, including that by the Climate Leadership Council for the United States.

Panel (b) shows that the net welfare effect of a global 30USD/t carbon price paired with carbon dividends would be progressive within all countries\(^{18}\). Even if lower income consumers experience a larger relative loss when expressed as share of their budget (Figure 1), the equal lump sum payments more then compensates them. Meanwhile, higher income consumers contribute more in absolute terms (Appendix Figure 9). This progressivity is more pronounced in more unequal countries that have a larger difference between the average consumer (who pays for the carbon dividend) and low-income consumers. It is important to clarify that the aggregate welfare effect remains negative in each country, once the relative effects in Figure 3 are weighted by income (Appendix Figure 9). But the median consumer is now better off in all 40 WIOD countries.

National progressivity of carbon dividends is unsurprising. But Panel (a) of Figure 3 shows that national dividends are also progressive globally. These results suggest two insights. First, national carbon dividends render the consumer cost of carbon pricing progressive—both within countries and globally. Second, a majority of consumers is better off with a carbon price plus dividend. Overall, 70% of consumers worldwide gain. Importantly, these results are based on revenue recycling by national governments and do not require any transfers between countries.

\(^{18}\)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—a consumption tax. Appendix Figure 11 shows that a similar pattern holds when we tax in the country where emissions occur in production.
Figure 3: Global price of 30 USD/t 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. 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 Scheme (ETS)

The European Union (EU) launched the EU Emissions Trading Scheme (ETS) on January 1, 2005. Much research has been devoted to its’ effectiveness, but less attention has been paid to how its’ costs may be distributed. I estimate the consumer cost of a stylized EU ETS. I again calibrate my model to 2004 and simulate a price of 30 USD/t in 27 EU ETS countries, levied on emissions in the sectors targeted by the ETS.

Figure 4a shows that the consumer cost appears regressive across the circa 490 million EU residents. Consumers in the bottom 10% of the EU income distribution incur a cost equivalent to 1-1.5% of expenditure. For the top half of the distribution, that cost is below 0.5%. Figure 4b again 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 if they have high or low incomes. This is again caused by dirtier value chains—especially energy utilities—in lower-income member states. Estonia is a case in point, where the high penetration of shale oil leads to especially large price increases.

It is important to note that my analysis is an ex ante evaluation of the EU ETS as it may have been intended. There are many reasons why the realized outcome may have differed. The EU ETS, and in particular the first phase, has been fraught by a range of implementation and design issues. A large literature documents these and evaluates the effects that the EU ETS had (Ellerman et al., 2016; Martin et al., 2016). Still, my results suggest one characteristic of the EU ETS which has received less attention—the possibly regressive effects across EU consumers, with a disproportionate cost to Eastern European and Baltic member states.

---

19 The price in the EU ETS fluctuated around 20-25 EUR/t throughout 2005, but many allowances were distributed free of charge. Due to oversupply, the price collapsed in 2007. Of 28 EU members in 2018, my sample contains 27. Bulgaria and Romania joined in 2007 and are included as EU ETS participants. So is the UK, which left in 2020. Only Croatia, which joined in 2013, is not. Non-EU participants Iceland, Liechtenstein and Norway are not in the sample.

20 The EU ETS covered about half of total CO₂ emissions, mostly in power generation and energy-intensive industries. To emulate the intended sector targeting of the first phase, 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”.

22
Figure 4: EU Emission Trading Scheme of 30 USD/t - 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 CO₂, 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).
4.3. Scenario 3: A Border Carbon Adjustment (BCA) in the EU

In a final scenario, I estimate the consumer cost from pricing the emissions content of traded goods. 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 help reduce the competitive pressure by adjusting prices of traded goods. They extend the coverage by levying tariffs on the emissions content of imports that do not face such a price at home (Felder and Rutherford, 1993). These can be complemented by appropriate rebates for exports. In theory, BCA are an elegant solution to the problem of carbon leakage (Markusen, 1975; Hoel, 1996). In practice, their potential for leakage reduction is debated and so is their legal status under the rules of free trade.

BCA feature in major policy proposals, including those by the Climate Leadership Council for the United States\(^\text{21}\) or the European Union’s Green New Deal\(^\text{22}\). 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. It is thus uniquely suited to investigate the consumer cost of BCA.

\(^{21}\)The Four Pillars of our Carbon Dividends Plan, https://clcouncil.org/our-plan/
\(^{22}\)EU Green Deal - Roadmap and key actions, https://ec.europa.eu/info/files/annex-roadmap-and-key-actions_en
Figure 5: EU Border Carbon Adjustment of 30 USD/t - 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 CO₂, 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).
I consider a BCA to complement a carbon price of 30 USD/t in the EU\textsuperscript{23}. The baseline is a carbon price of 30 USD/t on all emissions occurring in the EU. A second scenario adds to that a BCA—a carbon tariff on emissions imported into the EU and a tax exemption for exported emissions. Figure 5a shows shows the the net effect of BCA, which is difference between the two.

The consumer cost of such a BCA is rather small and is distributed with an inverse U-shape across the 490 million EU residents. Panel (a) shows that the largest cost falls on consumers at the bottom of the EU income distribution, equivalent to losing 0.5\% of expenditure. Panel (b) shows that the distribution within countries is again rather flat and has a mild inverted U-shape—consumers with the highest and lowest incomes are 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 than between them. This may be due to a relatively similar composition of aggregate imports into the different EU countries and income groups.

In sum, my simulations suggest a modest cost of BCA, at about 70 USD for the median EU consumer (Appendix Figure 10), which is distributionally neutral.

**Leakage reduction:** 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\textsuperscript{24}. I estimate that complementing the EU-wide carbon price with a BCA would have reduced global CO\textsubscript{2} emissions by an additional 0.7Gt compared to a global baseline of around 18Gt.

\textsuperscript{23}In the analysis of the EU ETS, I limited carbon pricing to emissions in energy-intensive sectors that were 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 sectors initially targeted by the EU ETS.

\textsuperscript{24}Studies using rich CGE models find 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.
5. Robustness

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

5.1. Consistency with consumer survey data

My demand side model follows 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. Simply put, because richer countries buy more textiles from the United States and fewer textiles from India, I expect consumers within countries to follow this pattern. This is of course a rather strong assumption. To test it, I compare my model estimates to a more conventional data source for distributional analysis—consumption surveys. Figure 6a compares my estimates of the consumer cost across income groups with survey-based estimates for China, India, Germany, Sweden, and the USA. I focus on the initial incidence, the cost of introducing the first 1 USD/t of a carbon price. 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 very similar estimates of the relative distribution of consumer cost from carbon pricing within countries, and maintain the relative differences between them. Still, I cannot deny the possibility that 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 data-driven in my framework, any potential bias in within-country estimates is unlikely to significantly alter the main results.

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25 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.
26 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). Consumption categories (600+ for USA, 106 for CHN/IND, 59 for DEU/SWE) are hand-matched to the 35 WIOD sectors and their domestic emissions intensities $e_{it}$.
**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.
5.2. Alternative input-output data (Eora)

The main results presented above are from calibrations using the World Input-Output Database (WIOD). WIOD provides harmonized data on 35 sectors in 40 countries (plus RoW). While it is one of the most commonly used sources for multi-regional input-output (MRIO) data, WIOD is subject to a number of limitations. To check for the robustness of my results, I re-estimate my headline result, this time calibrating my model using an alternative MRIO data source—the symmetric and harmonized version of Eora (Eora 26), which covers 189 countries and 26 sectors as recently as 2015.

Figure 6b compares estimates using Eora data to those using WIOD, both simulating the incidence of a global carbon price of 30 USD/t at the end of 2004 across the 40 WIOD countries. 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 consumer and producer 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$^{27}$ emitted from a larger range of activities (including land use). Reassuringly, the relative patterns look very similar.

Another drawback of WIOD is data availability. WIOD covers a large share of the world 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. And the most recent WIOD environmental accounts are for 2009. Eora meanwhile has data, though sometimes of less solid quality, for 189 countries and up to 2015. Appendix Figure 14 plots the global consumer cost of a global carbon price of 30 USD/t across all 189 countries in 2015. The results are again similar.

$^{27}$Specifically, the data includes six Kyoto gases and gas groups as reported in the PRIMAP-hist database: carbon dioxide (CO$_2$), methane (CH$_4$), nitrous oxide (N$_2$O), sulphur hexafluoride (SF$_6$), hydrofluorocarbons(HFCs), and perfluorocarbons (PFCs). Results look qualitatively similar if the analysis is restricted to CO$_2$ emissions from fossil-fuel combustion as reported by the IEA.
6. Conclusion

Using a structural model of the global economy, parameterized using bilateral trade data, I estimate the global consumer cost of carbon pricing. A global uniform carbon price is globally regressive. While within-country effects range from moderately progressive to moderately regressive, the global regressivity is almost entirely due to differences between countries. This is an important finding in light of the strong focus on within-country incidence in the literature to date. I show that these differences are driven mainly by 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 even globally. No transfers between countries are needed for this result.

Similar results apply to EU climate policy. The consumer cost of the EU ETS introduced in 2005 may have been regressive. This is again driven by differences between countries, with especially high costs to consumers in Eastern European and Baltic member states. My framework captures trade patterns and is thus well-suited to investigate carbon prices targeted at traded goods. A hypothetical Border Carbon Adjustment to complement an EU-wide carbon price generates rather low costs that follow an inverted U-shape—with the highest cost to consumers at either end of the EU income distribution.

My framework can in principle be calibrated to any global constellation of carbon prices, and using alternative data sources and parameter estimates. As any large-scale welfare analysis, my results rely on a number of assumptions and parameter estimates. I show that my findings replicate with an alternative data source and that they match well the evidence from consumer survey data.

Conceptually, I focus on the cost to consumers due to higher final goods prices. A complete welfare analysis of climate policy would require contrasting this consumer cost with the other costs and benefits of climate policy (Fullerton, 2011). First, the net costs of carbon pricing should be contrasted with the benefits of reduced climate damage (see Dietz et al., 2018, for a recent survey). Models that disaggregate the social cost of carbon (SCC)—the benefit of reducing CO₂ emissions by one unit today—suggest that climate mitigation is likely to disproportionately benefit countries that are simultaneously hot and poor (Dell et al., 2012; Burke et al., 2015; Ricke et al., 2018). This may represent a progressive force of carbon.
pricing. Second, the literature suggests that ‘source-side’ effects—the shift in industry composition and returns to factor inputs—may well be progressive, at least within countries (Goulder et al., 2019). But global trade dynamics may instead be regressive, as carbon pricing leads to a shift away from carbon-intensive sectors in developing countries. Further research is needed to determine the global “source-side” incidence of carbon pricing. I leave a systematic analysis of the net incidence of carbon pricing for future work.

Above all, my results support the notion that the distributional effect of carbon pricing ultimately depends on the use of revenues. This is in line with the within-country literature, which finds that energy taxes become less regressive, and even progressive, under lump-sum per capita rebates (Rausch et al., 2011; Williams et al., 2015) or other progressive measures such as food subsidies Gonzalez (2012). This is exactly what I find, with the important additional insight that no between-country transfers are required to make the consumer cost of carbon pricing progressive, even globally. This result may have potentially important implications for the equitable design of global climate policy.
References


Copeland, B. and Taylor, M. (1994). North-South trade and the environment. *Quar-


For Online Publication

The Global Consumer Incidence of Carbon Pricing: Evidence from Trade

APPENDIX

by Lutz Sager
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:

$$
v(x_h, p) = F \left( \frac{x_h}{a(p)} \right)^{\frac{1}{\alpha(p)}}
$$

(11)

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

$$a(p) = \exp \left( \alpha + \sum_{j=1}^{J} \alpha_j \log p_j + \frac{1}{2} \sum_{j=1}^{J} \sum_{k=1}^{J} \gamma_{jk} \log p_j \log p_k \right)
$$

(12)

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

(13)

A consumer $h$ chooses between $J$ goods and has indirect utility $v(x_h, p)$ which depends on her total expenditure budget $x_h$ and the vector of prices $p$. The additional assumptions on price aggregators $a(p)$ and $b(p)$ 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 $j$:

$$s_j(p, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{k=1}^{J} \gamma_{jk} \log p_k + \beta_j \log \left( \frac{x_h}{a(p)} \right)
$$

(14)

Expenditure of $h$ on good $j$ depends on preferences for good $j$ ($\alpha_j$), prices of all goods $k$ ($p_k$) and individual real income ($\frac{x_h}{a(p)}$). Key elasticities are the cross-price elasticities between goods $j$ and $k$ ($\gamma_{jk}$) and income (semi)-elasticities for each good $j$ ($\beta_j$). 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 $\sum_{j=1}^{J} \alpha_j = 1$, $\sum_{j=1}^{J} \beta_j = \sum_{j=1}^{J} \gamma_{jk} = 0$ and $\gamma_{jk} = \gamma_{kj}$ for all $j, k$. 
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:

\[
S_j = \alpha_j + \sum_{k=1}^{J} \gamma_{jk} \log p_k + \beta_j y
\]  

(15)

Aggregate expenditure shares resemble individual ones, but individual income is replaced by inequality adjusted real income \( y = \log \left( \frac{\bar{x}}{a(p)} \right) \). This is the price-adjusted version of the inequality-adjusted mean expenditure \( \bar{x} = \bar{x}e^\Sigma \) where \( \Sigma = E \left[ \frac{1}{N} \log \left( \frac{\bar{x}}{N} \right) \right] \) 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 \( j \) (\( \alpha_j \)) to differ between countries, but assume that consumers in all countries share the same price and income elasticities (\( \gamma_{jk} \) and \( \beta_j \)).

**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 \( \hat{\rho}_j = d\log(p_j) \) for all \( J \) goods and the log of expenditure \( \hat{x}_h = d\log(x_h) \). Fajgelbaum and Khandelwal (2016) show that the change in indirect utility is:

\[
\hat{v}_h = \sum_{j=1}^{J} \frac{\partial \log v(x_h, p)}{\partial \log p_j} \hat{\rho}_j + \frac{\partial \log v(x_h, p)}{\partial \log x_h} \hat{x}_h
\]  

(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:

\[
\hat{v}_h = \frac{\partial \log v(x_h, p)}{\partial \log x_h} \hat{\omega}_h
\]  

(17)

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

\[ \hat{\omega}_h = \sum_{j=1}^{J} (-\hat{p}_j) s_{j,h} + \hat{x}_h \]
\[ = \sum_{j=1}^{J} (-\hat{p}_j) S_j + \sum_{j=1}^{J} (-\hat{p}_j) (s_{j,h} - S_j) + \hat{x}_h \]
\[ = \hat{W} + \hat{\Psi}_h + \hat{x}_h \]  

(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 \( s_{j,h} - S_j = \beta_j \log \left( \frac{x_h}{\bar{x}} \right) \), to re-write the individual expenditure effect:

\[ \hat{\Psi}_h = - \left( \sum_{j=1}^{J} \beta_j \hat{p}_j \right) \log \left( \frac{x_h}{\bar{x}} \right) \]  

(19)

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

\[ \hat{\omega}_h = \hat{W} - \left( \sum_{j=1}^{J} \beta_j \hat{p}_j \right) \log \left( \frac{x_h}{\bar{x}} \right) + \hat{x}_h \]  

(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 $\phi_{kj}$. We furthermore 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 $C_j$:

$$\min C_j = \sum_k \phi_{kj} f_{kj} \quad \text{s.t.} \quad T_j \left( \sum_k a_{kj} \phi_{kj} \right)^{\sigma_j/(\sigma_j-1)} = X_j$$  \hspace{1cm} (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:

$$S_{kj} = \frac{\phi_{kj} f_{kj}}{C_j} = a_{kj} \phi_{kj}^{(1-\sigma_j)} P_j^{(\sigma_j-1)}$$  \hspace{1cm} (22)

The expenditure share of on input $k$ is decreasing in its price $\phi_{kj}$ relative to the input price index of sector $j$, $P_j = \left( \sum_k a_{kj} \phi_{kj}^{(1-\sigma_j)} \right)^{1/(1-\sigma_j)}$. 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 $k$, $c_{kj} = S_{kj} (1 - \kappa_j)$. This yields a linear relation between input and output in value terms:

$$x = Cx + y$$  \hspace{1cm} (23)

Here, $x$ is the $J$-vector of aggregate outputs in value terms (elements $p_j X_j$), $C$ is the $(J \times K = J^2)$-matrix of normalized input requirements $c_{kj}$ and $y$ 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.28

The Direct Requirement matrix \( C \) has element \( c_{kj} \) which is the dollar amount of intermediate input from industry \( k \) necessary for the production of a dollar of output in industry \( j \). Following Leontief (1970), the Total Requirement matrix \( T \) is:

\[
x = \left[ I - C \right]^{-1} y = Ty
\]  

(24)

Elements of \( T \), \( t_{kj} \), 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:

\[
e = T'd
\]  

(25)

The \( J \)-vector \( d \) of direct emissions intensities \( \delta_{j=k} \) describes for each sector the \( \text{CO}_2 \) emissions per dollar output. Element \( \varepsilon_j \) of \( e \) then summarizes the total \( \text{CO}_2 \) emissions intensity (tons of \( \text{CO}_2 \) 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 \( \varepsilon_j \). When evaluating carbon pricing scenarios, I simulate a new equilibrium input-output structure of the economy (\( C \) and \( T \)), which yields a new set of emissions intensities (\( e \)). These directly translate into final price changes seen by consumers.

**Price dynamics:**

For any given input-output structure, the emission intensity \( \varepsilon_j \) of final good \( j \) determines its relative price increase when we introduce a price on \( \text{CO}_2 \) emissions. When no input substitution takes place, this takes the following form.29

**Proposition 3 (Price effect without substitution)** Assume a carbon price \( \tau \) (in $ per ton of \( \text{CO}_2 \)) is introduced. Holding constant the structure of value chains \( C \) and hence the total emissions content of goods \( \varepsilon_j \), this will raise final prices to a new level \( p_{j}^{\text{new}} = (1 + \tau \varepsilon_j)p_j \).

This is the price increase predicted by standard MRIO methods that assume fixed proportion production functions (following Leontief, 1970). But I allow producers

28When 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.

29It 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.
to substitute intermediate inputs. This alters the structure of value chains and, consequently, emissions intensities $\varepsilon_j$. 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 ($k$).

**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 $\{c_{kj}\}$ and direct emissions intensities $\{\delta_j\}$, the new equilibrium production structure is defined jointly by:

$$c_{kj}^{new} = c_{kj} \left( \frac{\left( \sum_i a_{ij}(1+\tau_{ij}\varepsilon_i^{new})^{(1-\sigma_j)} \right)^{1/(1-\sigma_j)}}{1+\tau_{ij}\varepsilon_i^{new}} \right)^{\sigma_j} \forall k, j$$ (26)

$$e^{new} = [\left( I - C^{new} \right)^{-1}] d$$ (27)

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

$$S_{kj}^{new} = S_{kj} (1 + \tau j \varepsilon_k)^{(1-\sigma_j)} \left( \frac{p_{j}^{new}}{p_j} \right)^{(\sigma_j-1)}$$ (28)

Assuming unchanged value-added shares $\kappa_j$, we get an updated 'Direct Requirement Matrix' $C^{new}$ which has elements:

$$c_{kj}^{new} = \frac{S_{kj}^{new} p_{j}^{new}}{S_{kj} (1 + \tau j \varepsilon_k)^{(1-\sigma_j)} \left( \frac{p_{j}^{new}}{p_j} \right)^{(\sigma_j-1)}} c_{kj}$$ (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 $c_{kj}^{new}$ units (in PDU) of intermediate good $k$.

The "direct emissions intensity" $\delta_{kj}^{new} = \delta_j$ 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 $\varepsilon_j$ 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 $e^{new} = (I - C^{new})^{-1} d$ and the final goods price of $j$ including the carbon price is $1 + \tau e_j^{new}$. 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:

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

**Notes:** Overview of fuel type groupings used.

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): Coal-Oil ($\sigma^{CO} = 1.065$), Coal-Gas ($\sigma^{CG} = 1.426$), Coal-Electricity ($\sigma^{CE} = 0.866$), Oil-Gas ($\sigma^{OG} = 2.022$), Oil-Electricity ($\sigma^{OE} = 1.060$), and Gas-Electricity ($\sigma^{GE} = 1.099$).

Relative price changes of these fuels are based on their global average price (from the BP Statistical Review of World Energy 2017) and CO₂ 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 $\{\delta_j\}$, to be used in the above described process of intermediate input substitution.

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

1. Simulate new direct emissions intensities \( \delta_j^{new} \) after fuel substitution following the approach described in Appendix A.2.

2. Calculate initial total emissions intensities \( \{\varepsilon_j^{new}\} \) based on original production \( \{c_{kj}\} \) paired with updated direct emissions intensities \( \{\delta_j^{new}\} \).

3. Calculate initial price changes of intermediate inputs \( \hat{\phi}^{new}_{kj} \) based on \( \{\varepsilon_j^{new}\} \).
   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 \( \{c_{kj}^{new}\} \) based on these price changes \( \hat{\phi}^{new}_{kj} \).

5. Calculate updated total emissions intensities \( \{\varepsilon_j^{new}\} \) based on updated production \( \{c_{kj}^{new}\} \) paired with updated direct emissions intensities \( \{\delta_j^{new}\} \).

6. Repeat the loop through steps 3-5 until the additional adjustments in value chains become negligible, as defined by \( \sum \frac{|\Delta c_{kj}^{new}|}{c_{kj}} < \frac{1}{10,000} \).

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 data 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 \((\beta^s_i)\) 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:

\[
\gamma^{s',s}_{ii'} = \begin{cases} 
-\left(1 - \frac{1}{N}\right) \gamma^s & \text{if } i = i' \text{ and } s = s' \\
\frac{1}{N} \gamma^s & \text{if } i \neq i' \text{ and } s = s' \\
0 & \text{otherwise}
\end{cases}
\] (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 \((\gamma^s)\), I assume that trade costs between country-pairs \((t_{ni})\) are of the iceberg variety, implying \(p^s_{ni} = t_{ni}p^s_i\).

Specifically, I assume that bilateral trade costs between origin \(i\) and destination \(n\) are \(t_{ni} = d_{ni}^p \Pi_t \left(\delta^i_{g_{li,ni}}\right) \eta_{ni}\), where \(d_{ni}\) is bilateral distance and \(\rho\) 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:

\[
D_{ni} = \ln \left(\frac{d_{ni}}{d_{n}}\right) - \sum_{n'=1}^N \left(\frac{Y_{n'}}{Y_W}\right) \ln \left(\frac{d_{n'i}}{d_{n'}}\right)
\] (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 \(i\):

\[
S^s_{ni} = \frac{Y^s_i}{Y_W} + \alpha_i (S^s_n - S^s_W) - (\gamma^s \rho^s) D_{ni} + \sum_l (\gamma^s \delta^s_l) G_{l,ni} + (\beta^s_i - \alpha_i \bar{\beta}^s) \Omega_n + \varepsilon^s_{ni}
\] (32)
These aggregate expenditure shares \( S^s_{ni} \) 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 \( \frac{Y^s_i}{Y_w} \) and if consumers in \( n \) spend more on goods in sector \( s \) relative to the rest of the world \( (S^s_n - S^s_W) \). Variation in distance \( D_{ni} \) helps identify price elasticities \( \gamma^s \). 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 \( \Omega_n = y_n - y_W \) helps identify the income elasticities \( \beta^s_i \). 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. \( \Omega_n \) 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\(^{30} \), and that income is log-normally distributed. The Gini index is easily converted into the required Theil index\(^{31} \). Following the methodology of Fajgelbaum and Khandelwal (2016), I also proxy for the non-homothetic price index \( a(p) \) 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: \( \alpha_i \), \((\beta^s_i - \alpha_i \bar{\beta}^s)\), \((\gamma^s \rho^s)\). A second estimation equation helps to identify the missing parameters \( \bar{\beta}^s \). I estimate an Engel curve projecting aggregate expenditure shares in country \( n \) for sectors \( s \) on the inequality-adjusted real income \( y_n \):

\[
S^s_n = \alpha^s + \bar{\beta}^s y_n + \epsilon^s_n
\]  

(33)

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

---

\(^{30}\)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).

\(^{31}\)Assuming a log-normal distribution of expenditure with variance \( \sigma^2 \), the Theil index is \( \Sigma = \sigma^2 \), where the relation between \( \sigma^2 \) and the Gini coefficient \( G \) is given by \( \sigma^2 = 2 \left[ \frac{G+1}{2} \right]^2 \).
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 \( \sigma_j \) for each industry \( j \). CES production implies that producers in industry \( j \) spend the following share of their expenditures on intermediate inputs from industry \( k \):

\[
S_{kj} = \frac{\phi_{kj}f_{kj}}{P_jX_j} = a_{kj}\phi_{kj}^{(1-\sigma_j)}P_j^{(\sigma_j-1)}
\]  

(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 \( J \times K = 1400^2 = 1.96 \times 10^8 \) 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 competitive. I further assume that prices are the same for goods from sector \( s \) whether they are used as intermediates or final goods (\( P^s_i = \phi^s_i \)) and that traded goods are subject to iceberg trade costs \( t_{ni} \) between destination \( n \) and origin \( i \), \( P^s_{ni} = t_{ni}P^s_i \). Finally, I assume that production functions are identical for each destination sector \( j \) across countries \( n \) (\( \sigma_{n,j} = \sigma_j \) and \( a_{ni}^{s'j} = a_i^{s'j}, \forall n \)). Each sector \( s \) in destination \( n \) will then spend the following share on intermediate inputs from sector \( s' \) in origin \( i \):

\[
S_{ni}^{s'j} = a_{ni}^{s'j}(t_{ni})^{(1-\sigma_s)}(P_i^s)^{(1-\sigma_s)}(P_n^s)^{\sigma_s-1}
\]  

(35)

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

\[
\log(S_{ni}^{s'j}) = (1-\sigma_s)\log(t_{ni}) + (1-\sigma_j)\log(P_i^s) - (1-\sigma_j)\log(P_n^s) = (1-\sigma_s)\log(t_{ni}) + \lambda_n^s + \omega_i^{s'j}
\]  

(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 \( \sigma_s \). Again, I identify \( \sigma_s \) using cross-sectional variation in bilateral trade costs \( t_{ni} \) and assume that \( t_{ni} = d_{ni}^\rho \prod_l \left( g_{l,ni}\right) \eta_{ni}^{s'j} \), where \( d_{ni} \) is distance, \( \rho \) is the distance elasticity of trade costs, and \( g_{l,ni} \) are other gravity variables. The final estimating equation is:

\[
\log(S_{ni}^{s'j}) = (1-\sigma_s)\rho\log(d_{ni}) + \sum_l \left[ (1-\sigma_s)\delta_l G_{l,ni} \right] + \lambda_n^s + \omega_i^{s'j} + \epsilon_{ni}^{s'j}
\]  

(37)

Again, I obtain data on the 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 in-
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 ($\lambda_n^s$) and destinations ($\omega_{ji}^f$), as is common practice. Estimates are then consistent with alternative gravity set-ups that result in multiplicative bilateral resistance terms.
Table 3: Average estimates of income semi-elasticity of demand by country

<table>
<thead>
<tr>
<th>Country</th>
<th>( \hat{\beta} )</th>
<th>Country</th>
<th>( \hat{\beta} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS</td>
<td>0.017</td>
<td>IRL</td>
<td>0.000</td>
</tr>
<tr>
<td>AUT</td>
<td>0.002</td>
<td>ITA</td>
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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.
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<th>$\hat{\gamma}$</th>
<th>$\hat{\sigma}_s$</th>
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*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 5: Consistency of parameter estimates - $\hat{\beta}$

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

Table 6: Consistency of parameter estimates - $\hat{\gamma}$

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

Table 7: Consistency of parameter estimates - $\hat{\sigma}$

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</tbody>
</table>

Notes: Pairwise correlations, 35 CES elasticities estimated from (10), WIOD cross-sections.
D. Comparison to alternative modeling approaches

The results presented in this paper are based on a model of the global economy which incorporates adjustment margins both on the supply and the demand side. Figure 7 compares estimates. Much of the literature estimating the within-country incidence of energy taxes uses consumer expenditure micro-data (Grainger and Kolstad, 2010; Williams et al., 2015, e.g.). Often, a first approximation of the incidence can be based on the emissions-intensity of observed consumption. We have seen above that my global model produces similar results for the initial incidence of carbon pricing, at least for the United States. However, at higher prices we may expect divergence as my model allows consumers to shift away from emissions-intensive goods. Figure 7 compares estimates from my full model to such a simplified approach, ignoring both demand adjustments by consumers and input substitution by producers (dotted line). This would result in substantial over-estimation of the global consumer cost and its regressivity\textsuperscript{32}.

Meanwhile, an approach ignoring the within-country heterogeneity of consumers—assuming one representative consumer per county (dashed line)—produces estimates that are similar to the full model. This is in line with the above finding that the global incidence of carbon pricing is largely driven by between-country differences. To see this more clearly, we make use of Equation (2) to separate the variation in global consumer cost into two parts—the variation of average consumer cost between countries and the variation within countries around those averages. For the global uniform carbon price scenario, between-country variation accounts for 96\% of total variation of consumer cost\textsuperscript{33}.

\textsuperscript{32}The importance of incorporating behavioural responses has also been shown in the within-country incidence literature (West and Williams, 2004). Some contributions also incorporate general equilibrium dynamics to estimate the within-country incidence (e.g. Rausch et al., 2011)

\textsuperscript{33}Using Equation (2), the variation in cost to consumers $h$ in countries $n$ can be disaggregated as: $\text{Var} \left( \hat{\omega}_{n,h} \right) = \text{Var} \left( \hat{W}_n \right) + \text{Var} \left( \hat{\psi}_h \right)$.
Figure 7: Comparison of global incidence estimates by modelling choice

Notes: This figure shows the global distribution of the consumer welfare effect under a global uniform carbon price of 30 USD per ton of CO₂ simulated in 2004 (40 WIOD countries). The ‘default’ model replicates the results shown in Figure 1. The ‘extrapolated’ estimates are those from a naive model which calculates the welfare effect based on the observed emissions content of consumption multiplied with the carbon price, ignoring both demand adjustments by consumers and input substitution by producers. 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.
E. Additional figures for main results
Figure 8: Global price of 30 USD/t and national carbon dividend - 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 ($d_{ij}$) 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 (Panel a) and Figure 2 (Panel b).
**Figure 9:** Global price of 30 USD/t - Consumer cost [in absolute USD]

(a) Global price

(b) Global price + dividends

Notes: Absolute dollar values of consumer welfare effect under a global uniform carbon price of 30 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 (Panel a) and Figure 3 (Panel b).
Figure 10: EU ETS and BCA of 30 USD/t - Consumer cost [in absolute USD]

(a) EU Emission Trading Scheme

(b) EU Border Carbon Adjustment

Notes: Absolute dollar values of consumer welfare effect under two EU carbon pricing scenarios: 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 (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 Figure ?? (Panel a) and Figure ?? (Panel b).
Figure 11: 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 and ??, except that here the revenue is collected (and redistributed) in the country of the consumer, instead of where emissions occur in the value chain. 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).
F. Alternative carbon price of 100 USD/t in 2004

Existing carbon prices vary greatly in their level. There is even greater disagreement about the optimal level of a carbon price to account for the marginal external damage from another ton of emissions, the Social Cost of Carbon. Throughout the manuscript, I use a carbon price of 30 USD per ton of CO$_2$ in 2004 terms. Here, I replicate the key figures using a higher price of 100 USD per ton.

While the level of carbon price has potentially important consequences for the overall level of welfare effects, it does not appear to change any of the insights in this paper about how these costs are distributed.
Figure 12: 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 CO₂ 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 (Panel a) and Figure 3 (Panel b).
**Figure 13:** 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 CO₂, 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 CO₂, 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 Figure ?? (Panel a) and Figure ?? (Panel b).
G. Carbon Price in 189 Countries (Eora) - 2015

Figure 14: 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$_2$e) 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).