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The Global Consumer Incidence of Carbon Pricing: Evidence from Trade

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Abstract: The consumer cost of carbon pricing is globally regressive, more so across countries than within—it falls harder on average consumers in poor countries than on poor consumers in average countries. I show this using a novel, global approach to estimating the consumer incidence of carbon pricing. On the demand side, I allow consumption to differ both between countries and across income levels within them. On the supply side, I model substitution of inputs along global value chains. I identify all model parameters from data on bilateral trade flows. S imilar to a global carbon price, the introduction of the EU Emissions Trading System (ETS) in 2005 was likely regressive. The results are different for a carbon price on traded goods. The cost of a hypothetical Border Adjustment to complement the EU ETS follows an inverted U-shape—the richest and the poorest consumers in the EU incur the largest cost.

Keywords: Climate Policy; Environmental Equity; Environmental Tax; Environment and Trade; International Environmental Policy; Redistributive Effects.

JEL codes: F18, H23, Q52, Q56, Q58.

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1 Introduction

Governments around the world are introducing prices on carbon dioxide (CO₂) 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 2020, price coverage will exceed 20% with the launch of China's permit scheme (World Bank and Ecofys, 2018). Carbon pricing 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. In this paper, I estimate the global distribution of that cost to consumers due to higher prices. I show that the consumer cost of carbon pricing is globally regressive—it disproportionally affects poorer consumers—and more so between than within countries.

I 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 in the composition of aggregate consumption shape the consumer cost of carbon pricing. The same holds for differences in the fossil-fuel-intensity 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 tax incidence literature has largely focused on the within-country incidence of unilateral climate policy. But even coordinated domestic climate policy, as envisioned by the Paris Agreement signed in 2015, can have distributive effects across countries. This is particularly true considering that goods are often traded internationally and produced in globally connected value chains. The emergence of similar carbon pricing schemes around the world thus warrants a global approach to welfare analysis.

My results complement 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 of climate policy. The results can shed light on who may be prone to resisting climate policy and inform the design of more equitable policy. Ultimately, the incidence of any tax depends on how the collected revenue is used (Metcalf, 2009; Gonzalez, 2012). Knowing how to distribute this revenue, if indeed carbon pricing generates revenue, is an important reason to estimate the consumer cost incidence as I do.

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 between 40 countries and 35 industries from 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 parameterised 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 is the first to apply a non-homothetic gravity approach to the global incidence of carbon pricing.

On the supply side, I model substitution of intermediate inputs along global value chains. I also allow producers to substitute between primary fossil fuels used in production. Again, I use gravity equations to identify the relevant model parameters. I then simulate how a carbon price translates into changes in the structure of global production as emissions-intensive inputs become more expensive. My approach is a static one, 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. I show that a naive extrapolation based on the emissions content of consumption, while ignoring supply side adjustments, would significantly over-estimate the consumer cost.

I estimate the global consumer incidence of three carbon pricing scenarios. The first is a global uniform carbon price as prescribed by economic theory on efficiency grounds. I show that the consumer cost due to higher prices, 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 are much more important than those within countries in shaping the global incidence. These differences are due to the composition of aggregate consumption as well as the fossil-fuel-intensity of production. Put differently, carbon pricing affects average consumers in poor countries more than poor consumers in average countries.

A global uniform carbon price may not be a likely scenario in the near future. I thus investigate two further scenarios that are highly policy relevant. As a second scenario, I assess the introduction of the EU ETS in 2005. Similar to the global carbon price, I find that the EU ETS was likely regressive across the 490 million European consumers and that this incidence is largely driven by between-country differences—consumers in Eastern Europe and Baltic EU states are most affected. Finally, I investigate the consumer cost from introducing a carbon price on traded goods. Such Border Carbon Adjustments (BCA) 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 the EU ETS with BCA would most affect the poorest as well as the richest consumers in the EU. This time, the within-country variation in consumer cost dominates that between countries.

This paper contributes to three distinct literatures. First, it contributes to the literature on the incidence 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) summarises 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 paper 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.

Second, this paper 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 paper 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. This paper then contributes to the literature by providing the first estimate of the EU-wide consumer incidence of BCA to complement the EU ETS.

Third, this paper 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. Finally, Caron and Fally (2018) use a gravity approach to demonstrate the role of country-level income in shaping the CO₂-content of aggregate consumption. In this paper, 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 input-output methods.

2 Modelling the Global Consumer Cost of Carbon Pricing

I aim to estimate within a consistent framework how the consumer cost of carbon pricing is distributed across the globe—both between countries and at different income levels within countries. Such welfare analysis requires a description of consumer behaviour and preferences to capture how consumers adjust their consumption in response to changes in prices of final goods. In turn, changes in final goods prices are also influenced by how producers react to changes in the prices of inputs. In this section, I describe the theoretical framework that I use to model both demand and supply. In the next section, I describe how I estimate the key model parameters from data on bilateral trade flows.

2.1 Demand - A Global AIDS Demand System

The core of my analysis is an Almost Ideal Demand System (AIDS) which describes consumer behaviour and preferences. This demand system features non-homothetic preferences—expenditure shares of goods vary with consumer income. This is a key property which allows consumers at different income levels within countries to differ in their demand for emissions-intensive goods, which in turn determines their exposure to carbon pricing. The AIDS model was first proposed by Deaton and Muellbauer (1980) and is characterised by the following assumptions.

Assumption A1 (AIDS Consumer Preferences) We assume that the demand of consumer h for goods j is characterised by the family of log price-independent generalised preferences proposed by *Muellbauer (1975)*, where indirect utility takes the form:

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

We further assume that:

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

$$b(\mathbf{p}) = \exp\left(\sum_{j=1}^{J} \beta_j \log p_j\right)$$
(3)

A consumer *h* chooses between *J* goods and has indirect utility $v(x_h, \mathbf{p})$ which depends on her total expenditure budget x_h and the vector of prices \mathbf{p} . The additional assumptions on the price

aggregators $a(\mathbf{p})$ ("homothetic element") and $b(\mathbf{p})$ ("non-homothetic element"), close the description of the AIDS model.

These preferences yield the following expression for the expenditure share that consumer h spends on good j:

$$s_j(\mathbf{p}, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{k=1}^J \gamma_{jk} \log p_k + \beta_j \log \left(\frac{x_h}{a(\mathbf{p})}\right)$$
(4)

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

$$S_j = \alpha_j + \sum_{k=1}^J \gamma_{jk} \log p_k + \beta_j y$$
(5)

Aggregate expenditure shares resemble individual ones, but individual income is replaced by inequality adjusted real income $y = \log\left(\frac{\tilde{x}}{a(\mathbf{p})}\right)$. This is the price-adjusted version of the inequality-adjusted mean expenditure $\tilde{x} = \bar{x}e^{\Sigma}$ where Σ is the Theil index of the income distribution¹.

This aggregation property makes it possible to estimate demand parameters from aggregate expenditure data. I will do so following the procedure proposed by Fajgelbaum and Khandelwal (2016), which I describe in Section 3. Once estimated, 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 (γ_{jk} and β_j).

For each carbon pricing scenario, I can simulate the welfare effect to consumers at different income levels within each country. Here, I consider the Hicksian equivalent variation, which can be understood as the maximum amount of income that a consumer would be willing to give up for a price increase not to occur.

¹The Theil Index is defined as $\Sigma = \left[\frac{x_h}{\bar{x}} \log\left(\frac{x_h}{\bar{x}}\right)\right]$.

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

$$\hat{\omega}_{h} = \sum_{s=1}^{S} (-\hat{p}_{j}) S_{j} - \left(\sum_{s=1}^{S} \beta_{j} \hat{p}_{j}\right) \log\left(\frac{x_{h}}{\tilde{x}}\right) + \hat{x}_{h}$$

$$= \hat{W} + \hat{\psi}_{h} + 0$$
(6)

Proof. See Appendix A1, following directly Fajgelbaum and Khandelwal (2016). ■

The consumer 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 consumer h, $\hat{\psi}_h$. The individual cost $\hat{\psi}_h$ is a function of h's income (x_h) relative to the country's inequality-adjusted mean income (\tilde{x}) . Consumers with different income levels may be differentially affected by price changes because they have a different expenditure composition from the average consumer (driven by income elasticities β_j). Finally, \hat{x}_h is the income effect on h. I assume throughout that carbon pricing does not change incomes $(\hat{x}_h = 0)^2$. For non-marginal changes in prices $\hat{\mathbf{p}}$, equation (6) is integrated over the marginal welfare effect taking into account changes in expenditure patterns as well as constraining budgets shares to remain between 0 and 1.

Below, I parameterise a global version of this demand system using data on bilateral trade flows between 40 countries and 35 sectors. This is done by pairing the AIDS structure with the assumption of national product differentiation by country of origin (Armington, 1969). Hence, each sector *s* from country *i* sells a different product variety (implying that $J = S \times I$). This approach follows closely Fajgelbaum and Khandelwal (2016) who use it to estimate the distribution of the gains from trade (relative to counterfactual autarky). Applying the framework to estimating the global incidence of carbon pricing is one contribution of this paper. A non-homothetic gravity approach has previously been applied to the analysis of the CO₂ content of consumption by Caron and Fally (2018). They study how countries' per capita income levels relate to aggregate energy demand and CO₂ emissions. I demonstrate that such an approach can be useful in answering a different question, namely how the consumer cost of carbon pricing is distributed across the globe.

²There is evidence in the literature that the incidence of environmental policy may be altered when considering changes to factor incomes, including wages (Fullerton and Heutel, 2007, 2010; Rausch et al., 2011). However, in this paper I isolate the global distribution of consumer costs from higher prices.

2.2 Supply - Intermediate Inputs in Global Value Chains

Consumers are not the only ones affected by carbon pricing. Producers will see changes in the cost of inputs. In response, they will adjust the input mix, moving away from emissions-intensive inputs. This will in turn reduce the amount of emissions embodied in final goods and somewhat soften the effect of a carbon price on final goods prices. This dynamic applies to both intermediate and primary inputs. In this section, I discuss my approach to modelling substitution of intermediate inputs at a global scale. Substitution of primary inputs—in the form of fossil fuel combustion—is discussed in a later section. I derive a simple model of global value chains which allows for such input substitution and remains consistent with commonly used methods of input-output based emissions accounting. The supply side is characterised by a set of Constant Elasticity of Substitution (CES) production functions. These can again be parameterised using a structural gravity approach—this time using data on inter-industry trade flows.

Assumption A2 (CES Production Functions) We assume that all producers in each sector k have an identical Constant Elasticity of Substitution (CES) production function across J intermediate inputs with prices ϕ_{jk} . We further assume perfect competition and constant returns to scale in all sectors. Producer input choices in each sector can then be represented by a representative producer minimising input cost C_k :

$$\min C_k = \sum_j \phi_{jk} f_{jk} \quad s.t. \ T_k \left(\sum_j a_{jk}^{1/\sigma_k} f_{jk}^{(\sigma_k - 1)/\sigma_k} \right)^{\sigma_k/(\sigma_k - 1)} = X_k \tag{7}$$

For any level of output X_k , producers minimise input costs C_k . The expenditure share on input *j* among expenditures for all intermediate inputs is given by:

$$S_{jk} = \frac{\phi_{jk} f_{jk}}{C_k} = a_{jk} \phi_{jk}^{(1-\sigma_k)} P_k^{(\sigma_k-1)}$$
(8)

 P_k is the producer input price index of sector k given by $P_k = (\sum_j a_{jk} \phi_{jk}^{(1-\sigma_k)})^{1/(1-\sigma_k)}$. Constant returns to scale along with perfect competition imply that input shares and output prices are independent of final demand. There is thus no need for an explicit characterisation of an equilibrium price condition.

Below, I discuss how I estimate the relevant substitution elasticity σ_k using a structural gravity approach based on bilateral inter-industry trade flows between pairs of 1400 (K = J = 40 countries × 35 sectors) sectors³. Once elasticities are estimated, I can simulate input substitution dynamics based on a framework that is consistent with the structure of input-output matrices. The supply side dynamics render the welfare analysis more realistic, as we may expect significant adjustments to occur before products reach final consumers. However, the key strength of my model remains the global demand system geared at distributional welfare analysis.

My approach follows other structural gravity approaches geared at environmental policy analysis (e.g. Shapiro, 2016; Larch and Wanner, 2017)⁴. The key difference is my focus on the consumer incidence both between and within countries, which is made possible by the non-homothetic gravity approach introduced by Fajgelbaum and Khandelwal (2016).

2.3 Supply - Input-output structure

On the supply side, I model the flow of intermediate inputs within and between countries—the input-output linkages characterising the structure of the world economy. The importance of accounting for the structure of production for welfare analysis has been demonstrated by Caliendo and Parro (2015). In the context of NAFTA, they find that modelling input-output linkages is important to fully capture the welfare gains from tariff reductions. My approach to supply side modelling exploits the MRIO structure provided by WIOD. It thus remains consistent with MRIO-based methods of accounting for indirect emissions, which are often applied in the literature to characterise the indirect emissions embodied in consumption (e.g. Sager, 2017; Levinson and O'Brien, 2018). The above CES production technologies translate into the input-output framework as follows.

Total expenditure on all intermediates by sector k is $C_k = P_k X_k$. The difference between the final price p_k for one unit of good k and required input expenditures defines the value added share $\kappa_k = \frac{p_k - P_k}{p_k}$. Each dollar value of output in sector k then uses an average amount of dollar value inputs from sectors j, $c_{jk} = S_{jk}(1 - \kappa_k)$. All output is either used as intermediate input into another sector or as final consumption. This yields a linear relation between input and output in value terms:

$$\mathbf{X} = \mathbf{C}\mathbf{X} + \mathbf{y} \tag{9}$$

³One limitation of using WIOD data is that I cover only 35 sectors of the economy. As such, I will be able to estimate and simulate substitution between inputs from these 35 sectors. I do not 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 harmonised multi-regional input-output (MRIO) accounts and substitution between the 35 sectors should already capture a significant portion of input substitution.

⁴Shapiro (2016) applies a structural gravity approach to model the CO₂ content of transportation—both international and intranational. He finds that the global gains from trade vastly exceed the costs due to CO₂ emissions. Larch and Wanner (2017) focus on carbon tariffs and find that these indeed hold the potential to reduce leakage at a global scale.

Here, **X** is the *K*-vector of aggregate outputs in value terms (elements $p_k X_k$), **C** is the (*K* × *K*)-matrix of normalised input requirements c_{jk} and **y** the *K*-vector of final consumption again in value terms (elements $p_k y_k$). 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. In a prominent example, Acemoglu et al. (2012b) use such a linear mapping to describe the network structure of an economy with Cobb-Douglas technologies⁵.

The Direct Requirement matrix **C** has element c_{jk} which stands for the dollar amount of direct input from industry *j* necessary for the production of a dollar output in industry *k*. Following Leontief (1970), we derive the Total Requirement matrix **T**:

$$\mathbf{T} = \left[\mathbf{I} - \mathbf{C}\right]^{-1} \mathbf{y} \tag{10}$$

Elements of **T**, t_{jk} , describe the dollar amount of total input from sector j embedded in a dollar of final consumption from sector k, taking into account all upstream processes. Total input requirements can then be translated into total emissions intensities which are frequently used in the literature on consumption-based emission accounting. The *J*-vector **d** of direct emissions intensities δ_j describes for each sector the CO₂ emissions per dollar output. It translates into total emissions as follows:

$$\mathbf{e} = \mathbf{T}'\mathbf{d} \tag{11}$$

Element ε_k of **e** then summarises the total CO₂ emissions content (*tCO*₂/*USD*) of final consumption from sector *k*, including all upstream emissions in sectors *j*. The effect on final prices due to a price on carbon emissions will be a function of these total emission intensities ε_k .

⁵When technologies are of the Cobb-Douglas variety, *C* is constant for all price combinations (as in Acemoglu et al., 2012b, and many other applications). I add further flexibility in input substitution by modelling CES technologies, which means that *C* adjusts when input prices change. This reduces analytical tractability, but adds what I think is important flexibility when analysing carbon pricing. I approximate the adjustment of inputs recursively as described in Appendix A3.

2.4 Supply - Price Dynamics

For any given input-output structure, the emission intensity ε_k of final good *k* determines its relative price increase when we introduce a price on CO₂ emissions. When no input substitution takes place, this takes the following form⁶.

Proposition 2 (Price effect without substitution) Assume a carbon price τ is introduced (in this case USD/tCO_2). Holding constant the structure of value chains **C** and hence the total emissions content of goods ε_k , this will raise final prices to a new level $p_k^{new} = (1 + \tau \varepsilon_k)p_k$.

This is the price increase predicted by standard MRIO methods that assume fixed proportion production functions. But I allow producers to substitute intermediate inputs. This alters the structure of value chains and, consequently, emissions intensities ε_k . This invites yet further adjustments to inputs until a new equilibrium is reached. I also allow carbon prices to differ between goods *j*.

Proposition 3 (Price effect with input substitution) Assume a set of carbon prices $\{\tau_{jk}\}$ on intermediate goods j used in production k is introduced. Given initial input requirements $\{c_{jk}\}$ and direct emissions intensities $\{\delta_j\}$, the new equilibrium production structure is defined jointly by:

$$c_{jk}^{new} = \left(\frac{\sum\limits_{i}^{k} (1+\tau_{ik}\varepsilon_{i}^{new})^{(1-\sigma_{k})})^{1/(1-\sigma_{k})}}{1+\tau_{jk}\varepsilon_{j}^{new}}\right)^{\sigma_{k}} c_{jk} \forall k, j$$
(12)

 $\mathbf{e}^{new} = \left[(\mathbf{I} - \mathbf{C}^{new})^{-1} \right]' \mathbf{d}$ (13)

Proof. See Appendix A2. ■

The procedure yields a new set of final goods prices, which consumers face under carbon pricing. For each carbon pricing scenario, I approximate numerically the new equilibrium supply chain structure \mathbf{C}^{new} , emission intensities ε_k^{new} and prices p_k^{new} . The procedure is described in Appendix A3.

⁶It 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 internalise carbon prices even if they were to be levied at the point of sale.

2.5 Supply - Fuel Switching

As described above, producers will react to carbon pricing by reducing the share of CO₂ intensive intermediate goods. This changes the supply chain structure C^{new} and, as a result, total emissions embodied in products j, ε_j . This captures the reaction of producers to the extra cost from emissions generated by suppliers. But of course, producers may also reduce emissions that are directly generated during their own production processes.

To model this, I exploit the specific structure of environmental accounts in WIOD. Input-output tables capture all transactions between sectors in value terms and are ideally suited to trace the flow of intermediate goods. The WIOD environmental satellite accounts provide information on CO_2 emissions by sector and energy commodity. They capture emissions only in that sector where emissions occur, i.e. where fossil fuel is combusted (Genty et al., 2012). I use this two-tier reporting of transactions in value terms and emissions where they occur to separate switching of intermediate inputs and substitution of direct fossil fuel inputs. Before modelling adjustments in intermediate inputs **C** and thus total emissions intensities ε_j , I allow producers to adjust the mix of fossil fuels used directly in production. This alters direct emission intensities δ_j , which then feed into the adjustment of value chains.

Here, I assume that production of a unit of output requires energy services generated from a constant elasticity of substitution (CES) production function using three fuel inputs—coal, oil and gas^7 —to produce energy services to be combined with intermediate inputs. Again, the representative producer in industry *k* minimises direct input costs of fuels for a given level of energy services output. Analytically, this is identical to intermediate input choice in (8).

The key assumption is that the total amount of energy services necessary to produce one unit of output in each sector remains the same. But producers can shift between the fossil fuels they use to generate these energy services. In all simulations, the most important instance of fuel switching occurs in the electricity sector, where gas is substituted for coal when carbon is priced. This reduces the direct emission intensity (δ_j^{new}) of the electricity sector and in turn lowers the indirect emission intensity (δ_j^{new}) of the electricity at some point in their value chain.

⁷I use WIOD data on energy-related emissions in three fuel groups: coal, oil and gas. Coal: anthracite, lignite and coke; Oil: gasoline, Diesel, jet kerosene, LFO, HFO and naphtha; Gas: natural and other gas.

3 Estimating Model Parameters

To calibrate the above models of demand and supply, I use data on bilateral trade flows between 40 countries and 35 sectors from the World Input-Output Database (WIOD). I identify the parameters of the demand system using data on bilateral trade of final goods and the parameters of production functions using data on bilateral inter-industry trade.

3.1 Demand - Estimating Demand System Parameters

To identify the parameters of the demand system I follow Fajgelbaum and Khandelwal (2016) in embedding the AIDS demand structure in a multi-sector Armington model of international trade of final goods. The model allows for goods within each sector to be differentiated by country of origin and it also allows for cross-country differences in sectoral productivity and trade cost. Essentially, each sector from each country sells a different variety. This translates into 1400 varieties (K = J = 40×35 in the above notation). Consumers in destination country *n* consume goods from sector *s* and origin country *i*.

To characterise demand responses and welfare effects for households *h* in country *n*, I thus require values for the 1400 income semi-elasticities for each variety (β_i^s) and 35 sector-level price elasticities (derived from γ^s). I follow Fajgelbaum and Khandelwal (2016) in assuming that there is symmetric substitution within each sector *s* between goods from different countries *i*, but no substitution between sectors:

$$\gamma_{ii'}^{ss'} = \begin{cases} -\left(1 - \frac{1}{N}\right)\gamma^s & \text{if } i = i' \text{ and } s = s'\\ \frac{1}{N}\gamma^s & \text{if } i \neq i' \text{ and } s = s'\\ 0 & \text{otherwise} \end{cases}$$
(14)

Consumers can substitute textiles from the United States with textiles from India, but they cannot substitute textiles with minerals. Trade costs between country-pairs are of the iceberg variety, implying the typical no-arbitrage condition:

$$\frac{P_{ni}^s}{p_i^s} = t_{ni} \tag{15}$$

Specifically, I assume that bilateral trade costs between origin *i* and destination *n* are $t_{ni} = d^{\rho} \prod_{l} \left(g_{l,in}^{\delta_{l}}\right) \eta_{ni}$, where d_{ni} is distance and ρ is the distance elasticity of trade costs. Other bilateral gravity characteristics are in $g_{l,ni}$. The system results in the following estimating equation for the

aggregate expenditure of goods from sector s and country i by consumers in country n:

$$S_{ni}^{s} = \frac{X_{ni}^{s}}{Y_{n}} = \frac{Y_{i}^{s}}{Y_{W}} + \alpha_{i}(S_{n}^{s} - S_{W}^{s}) - (\gamma^{s}\rho^{s})D_{ni} + \sum_{j}(\gamma^{s}\delta_{j}^{s})G_{j,in} + (\beta_{i}^{s} - \alpha_{i}\overline{\beta}^{s})\Omega_{n} + \varepsilon_{ni}^{s}$$
(16)

Aggregate expenditure shares (S_{ni}^s) are observed in WIOD (bilateral trade flows in final consumption). As proxies for bilateral trade cost, I use data from CEPII's Gravity database on the bilateral distance between country pairs (D_{ni}) , as well as indicators for common language and a shared border $(G_{j,in})$. Variation in the inequality-adjusted mean income of country *n* relative to the world $(\Omega_n = y_n - \overline{y}_W)$ helps identify the income elasticities (β_i^s) . Ω_n is calculated using country-level population and income (GDP) from the Penn World Tables and the Gini index of income inequality from the World Income Inequality Database (WIID). I assume a constant savings rate, which implies that expenditure x_h is proportional to income⁸. Assuming a log normal income distribution, the Gini index is easily converted into the required Theil index⁹. Following the methodology of Fajgelbaum and Khandelwal (2016), I also proxy for the non-homothetic price index $a(\mathbf{p})$ with a Stone price index for each destination country *n* using quality-adjusted prices as provided by Feenstra and Romalis (2014).

From the estimation of (16), I identify the following parameter estimates: $\hat{\alpha}_i$, $(\beta_i^s - \alpha_i \overline{\beta}^s)$, $(\gamma^s \rho^s)$. A second estimation equation helps to identify the missing parameters $\overline{\beta}^s$. I estimate an Engel curve projecting aggregate expenditure shares in country *n* for sectors *s* on the adjusted real income *y_n*:

$$S_n^s = \alpha^s + \overline{\beta}^s y_n + \varepsilon_n^s \tag{17}$$

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

⁸Basing 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).

⁹Assuming a log-normal distribution of expenditure with variance σ^2 , the Theil index is $\sum = \frac{\sigma^2}{2}$ where the relation between σ^2 and the Gini coefficient *G* is given by $\sigma^2 = 2\left[\frac{G+1}{2}\right]^2$.

3.2 Supply - Estimating Production Function Parameters

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

$$S_{jk} = \frac{\phi_{jk} f_{jk}}{P_k X_k} = a_{jk} \phi_{jk}^{(1-\sigma_k)} P_k^{(\sigma_k-1)}$$
(18)

I consider bilateral inter-industry trade flows between 1.96m (1400²) industry pairs—destination sector *k* in country *n* from origin sector *s* in country *i*. Assume again 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 assume that prices are the same for goods from sector *s* whether they are used as intermediates or final goods $(p_i^s = \phi_i^s)$ and that traded goods are subject to iceberg trade costs t_{in} between destination *n* and origin *i*, $p_{in}^s = t_{in}p_i^s$. Finally, I assume that production functions are identical for each destination sector *k* across countries *n* ($\sigma_{n,k} = \sigma_k$ and $a^k s_{in} = a^k s_i$, $\forall n$). Each sector *k* in destination *n* will then spend the following share on intermediate inputs from sector *s* in origin *i*:

$$S_{in}^{ks} = a_i^{ks}(t_{in})^{(1-\sigma_k)}(p_i^s)^{(1-\sigma_k)}(P_n^k)^{(\sigma_k-1)}$$
(19)

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

$$\log\left(S_{in}^{ks}\right) = \log\left(a_i^{ks}\right) + (1 - \sigma_k)\log\left(t_{in}\right) + (1 - \sigma_k)\log\left(p_i^s\right) - (1 - \sigma_k)\log\left(P_n^k\right)$$

$$= (1 - \sigma_k)\log\left(t_{in}\right) + \lambda_n^k + \omega_i^s$$
(20)

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 preferences¹⁰.

I use this simple gravity equation to estimate the sector-specific CES production elasticities σ_k . I assume again that $t_{in} = d_{in}^{\rho} \Pi_l \left(g_{l,in}^{\delta_l} \right) \eta_{in}^{ks}$, where d_{in} is distance, ρ is the distance elasticity of trade costs, and $g_{l,ni}$ are other gravity variables. The final estimating equation to identify σ_k using

¹⁰Anderson and Van Wincoop (2003) use market clearing conditions and assumptions of symmetry to transform equation (19) into a gravity equation as a function of equilibrium price indices, or "multilateral resistance" terms. I replace multilateral resistance terms with fixed origin and destination fixed-effects as is commonly done. As such my estimates would also be consistent with alternative derivations of gravity equations which result in a multiplicative form of bilateral resistance.

cross-sectional variation in bilateral trade costs t_{in} .

$$\log\left(S_{in}^{ks}\right) = (1 - \sigma_k)\rho\log\left(d_{in}\right) + \sum_l \left[(1 - \sigma_k)\delta_l\log G_{l,in}\right] + \lambda_n^k + \omega_i^s + \varepsilon_{in}^{ks}$$
(21)

Again, I obtain data on the bilateral distance between country pairs (d_{in}) from CEPII. The other elements of $G_{l,in}$ are indicators for common language and a shared border, also from CEPII. I estimate this equation separately for the 35 industries k^{11} .

¹¹For 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 $\rho = 0.177$.

3.3 Model Overview and Parameter Estimates

Table 1 provides an overview of the key model components. The key advantage of my approach is that it makes possible welfare analysis across consumers in different countries and at different income levels within countries. This is done by modelling consumer preferences within an Almost Ideal Demand System (AIDS). The AIDS structure allows for non-homothetic preferences—expenditure shares differ along the income distribution. This is captured by the 1400 origin-sector specific income semi-elasticities ($\hat{\beta}_i^s$). My approach also captures some important margins for adjustment that are important in estimating the consumer cost of carbon pricing. The demand structure allows consumers to substitute away from dirty goods when carbon pricing raises their relative price. This is captured by the 35 price elasticity parameters (γ^s). These parameters are estimated from equations (16) and (17) using WIOD data on bilateral trade in final consumption.

On the supply side, I model production in each sector by a separate Constant Elasticity of Substitution (CES) production function using intermediate inputs. This allows producers to substitute away from dirty intermediate goods when prices rise. I also allow producers to reduce emissions from their production process directly by substituting between the three primary fossil fuel groups—coal, gas and oil. Equation (21) yields estimates of the 35 CES elasticities (σ_k) describing producers in sectors *k*. These are estimated from data on inter-industry trade flows. The Appendix provides an overview of some of these parameter estimates. Estimated parameters are highly consistent across different years¹².

	Theory	Estimation	Data
Demand	AIDS preferences (non-homothetic)	Income elasticities $(\hat{\beta}_i^s)$ Price elasticities (γ^s)	WIOD: bilateral trade, final cons. (35 sectors, 40 countries, 1996-2009)
Supply: Input substitution	CES production (per sector)	CES elasticities (σ_k)	WIOD: bilateral inter-industry trade (35 sectors, 40 countries, 1996-2009)
Supply: Fuel switching	CES production (per sector)	CES elasticities (σ_k)	WIOD: fossil-fuel energy shares (coal, gas, oil)

 Table 1: Method Overview

Note.-This table provides a brief overview of the key model characteristics and data sources.

¹²For 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.

The relative importance of the different adjustment margins of demand and supply can be demonstrated using the results of counterfactual carbon pricing scenarios. Figure 1 summarises the predicted potential for global CO₂ emissions reductions under different levels of a global uniform carbon price. This price applies to all goods, traded and non-traded. I use 2004 as a base year as it was before any major carbon pricing scheme had been introduced in any of the 40 countries. In the year 2004, we start out with 20.4 Gt of total CO₂ emissions in the 40 WIOD countries¹³. The predicted emissions reduction from demand responses is limited. At a carbon price of 30 USD/t, I estimate that total emissions would be reduced by 2.5 Gt to 17.9 Gt by demand response alone. This reduction is mostly due consumers substituting away from emissions-intensive goods. A small portion is due to reduced spending power from across the board price increases.

[Figure 1 about here.]

Allowing for substitution of intermediate inputs increases the emissions reduction potential of carbon prices. At a global carbon price of 30 USD/t, I estimate that input substitution adds a further 4.9 Gt in annual emissions reductions. Finally, I estimate that fuel switching adds a further 0.6 Gt in annual emissions reductions. For the rest of this paper, I focus on results which allow for fuel switching and input substitution before carbon prices are passed on to end consumers.

These supply-side dynamics significantly mitigate the price increase passed on to consumers and render the incidence estimates more realistic. Nevertheless, I exclude some margins of adjustment that may be important. I assume perfect competition and thus can model neither the possibility of imperfect pass-through of carbon prices (Ganapati et al., 2016), nor the potential for competitive price adjustments in the market for fossil fuels. While I allow for fossil fuel switching, I ignore the potential to replace fossil fuels with renewable energy sources. My model is static and assumes a constant technologies in production, both across intermediate and fossil fuel inputs. This means that I exclude the possibility that carbon pricing induces energy-saving innovation in production (Aghion et al., 2016). I also ignore the possible repercussions for factor incomes to households (Rausch et al., 2011). Finally, I estimate the consumer cost due to higher prices only. Ultimately, the welfare effects of carbon pricing might be mitigated through the redistribution of collected revenue in the form of income tax cuts or lump-sum transfers (West and Williams, 2004). We may expect that ignoring these margins of adjustment biases the results presented in this paper only as long as any such adjustment systematically falls on either richer or poorer consumers.

¹³This amount may differ from other aggregate emissions numbers for various reasons. Most importantly, WIOD only covers 40 countries and environmental satellite accounts do not include emissions from land conversion.

4 Results for the Global Consumer Cost of Carbon Pricing

Once calibrated, I use my model to estimate the gobal consumer cost under three counterfactual carbon pricing scenarios. Economic theory recommends meeting the global climate externality with a global carbon price. As a first scenario, I thus simulate a world in which all 40 countries in my sample implement a uniform price on carbon emissions. I choose 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). While the global uniform price may not be a realistic scenario in the near future, an EU-wide carbon price is already operational. The second scenario is thus the introduction of the EU ETS in 2005. Finally, I simulate the cost to European consumers of complementing the EU ETS with Border Carbon Adjustments (BCA) that target the emissions content of imported goods.

4.1 Scenario 1 - A Global Uniform Carbon Price

I estimate the consumer cost from introducing a global uniform carbon price of 30 USD/t¹⁴.

[Figure 2 about here.]

Figure 2 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 countries contained in the sample in 2004. The dashed line shows estimates for the average consumer cost as a share of annual expenditure for each percentile. The solid line shows a 10th degree polynomial approximation thereof. The blue band represents 95% confidence intervals¹⁵. The first insight from this analysis 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 is more than twice as large as that of consumers in the top 10 %.

[Figure 3 about here.]

A second insight is that the distributional incidence can differ between countries. To see this, Figure 3 displays the distribution of the consumer cost within each of the 40 countries. Each line represents the average cost to consumers at different percentiles of the within-country

¹⁴Some may argue that a carbon price of 30 USD/t of CO_2 is low compared to estimates of the climate externality. I show in Appendix 5 that, while the overall cost is higher, the relative incidence of a carbon price of 100 USD/t is highly similar to the results reported here for 30 USD/t.

¹⁵Confidence intervals are from 500 separate simulations, each using a different set of model parameters drawn from the joint normal distributions for parameter estimates from estimations (16), (17) and (21).

income distributions. Upward-sloping lines suggest that in those countries carbon pricing is more regressive—with larger relative costs to lower income consumers—and vice versa. The distributional incidence of carbon pricing in richer nations—such as Germany, Sweden and the United States—appears to be more regressive. Meanwhile the incidence in large developing nations—such as China and Indonesia—looks somewhat progressive. These stylised patterns are in line with the within-country incidence literature, which finds weak to moderate regressivity in rich countries (Poterba, 1991; Grainger and Kolstad, 2010) and progressivity in poor countries (Datta, 2010; Sterner, 2012). However, Figure 3 also suggests a third, more nuanced insight. The slope of individual lines in Figure 3 is much less important than the distances between the lines. The consumer incidence of carbon prices varies much more strongly between than within countries.

[Figure 4 about here.]

Figure 4 plots for each country the average consumer welfare loss from a global carbon price of 30 USD per ton of CO_2 against the average expenditure level per capita. The between country incidence of a global carbon price is clearly regressive. The average consumer welfare loss in China is estimated to be roughly four times as large as that in rich nations such as Sweden and France. This is driven both by a more emissions-intensive mix of consumption (Caron and Fally, 2018) and more emissions-intensive value chains in production (Copeland and Taylor, 1994; Levinson, 2009). It has been long recognised that differences in economic structure between countries have important repercussions for environmental policy (Whalley and Wigle, 1991; Shah and Larsen, 1992). My analysis suggests that these differences between countries are more important for the global incidence of carbon pricing than differences within countries.

[Figure 5 about here.]

Finally, Figure 5 translates the relative consumer cost from Figure 2 into absolute dollar values. While carbon pricing results in a larger relative cost for poor consumers, the absolute cost is still largest for consumers with the highest incomes. Put differently, the unequal distribution of consumption expenditures across the global results in rich consumers paying the bulk of the absolute cost of pricing carbon.

4.2 Scenario 2 - The EU Emissions Trading Scheme (ETS)

The European Union (EU) introduced the EU Emissions Trading Scheme (ETS) in 2005. This scheme was the first coordinated carbon pricing scheme by a group of developed countries. Of the 28 current EU member states, my sample includes 27 (all except Croatia which joined in 2013)¹⁶. I calibrate my model to 2004, the year before the introduction of the EU ETS, and estimate the consumer cost of introducing a uniform carbon price in these 27 countries. The price in the EU ETS fluctuated mostly around 20-25 EUR/t throughout 2005. I simulate a carbon price of 30 USD/t in all industries of the 27 EU member countries¹⁷.

[Figure 6 about here.]

Figure 6 shows how the estimated consumer cost due to higher prices is distributed across the 490 million EU residents. The overall consumer cost of a EU wide carbon price of 30 USD/t appears more regressive. Consumers in the bottom 10 % of the EU income distribution incur a cost equivalent to around 2% of their total expenditure. The cost to consumers in the top half of the income distribution is less than 1%.

[Figure 7 about here.]

Again, the distribution of consumer cost is largely driven by differences between countries rather than within. Figure 7 shows the distribution of consumer cost in the 27 EU member states. Just like for the global carbon price, we see only modest variation in the distributional incidence within countries, but a larger difference between EU member states.

[Figure 8 about here.]

Figure 8 shows the average consumer cost across countries. Clearly, such a carbon price has a much larger welfare effect on the average consumer in lower income countries among the 27 EU member states. The largest welfare loss occurs for consumers in the Eastern European and Baltic states. Again, this regressive incidence of an EU carbon price is due to a dirtier consumption mix of lower-income consumers as well as higher emissions intensities of industries in lower-income

¹⁶Among the 28 EU member states in 2018, Bulgaria and Romania joined in 2007. Croatia joined in 2013. Bulgaria and Romania are included here as participants of the EU ETS. In addition to the 28 EU member states, the EU ETS also operates in Iceland, Liechtenstein and Norway, which are not in the sample.

¹⁷The first phase of the EU ETS, running from 2005 to 2007, was considered a learning phase. It covered about half of total CO_2 emissions, mostly in power generation and energy-intensive industries. Almost all allowances were initially distributed free of charge based on estimates. Due to oversupply, the allowance price collapsed in 2007.

countries. As expected, the policy has close to no cost to consumers in countries outside of the 27 EU states.

[Figure 9 about here.]

While the relative consumer cost is regressive, the absolute monetary welfare losses are again much higher for consumers at the upper end of the income distribution. This is shown by Figure 9. The median EU consumer incurs a welfare loss of ca. 190 USD from an EU-wide carbon price of 30 USD/t in 2004.

4.3 Scenario 3 - Border Carbon Adjustments to complement the EU ETS

Finally, I estimate the consumer cost from pricing the emissions content of traded goods. An important concern for countries considering to introduce a carbon price is that it may weaken competitiveness of domestic industries relative to foreign industries subject to less stringent policy. As a result, we may see carbon leakage—emissions simply move abroad instead of being avoided altogether (Levinson and Tayler, 2008; Aichele and Felbermayr, 2015; Fowlie et al., 2016). This dynamic can be countered with Border Carbon Adjustments (BCA). BCA are most commonly proposed in the form of carbon tariffs on the embodied carbon of imported goods. They target goods from countries with less stringent carbon pricing regimes (Felder and Rutherford, 1993).

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. They too may increase consumer prices, this time, however, for imported goods. Despite their theoretical appeal, there is to date scarce evidence on the welfare effects of BCA. My framework combines distributional welfare analysis with an explicit model of trade flows and global value chains. It is thus uniquely suited to investigate the consumer incidence of BCA. I consider a second scenario, in which the carbon price of 30 USD/t in the EU is extended to traded goods.

[Figure 10 about here.]

Figure 10 shows how the cost of complementing the EU ETS with a BCA is distributed. Across the 490 million residents of the EU, I estimate that welfare losses follow an inverse U-shape. Contrary to the internal carbon price, the cost of a BCA varies more strongly within countries than between them. Overall, the consumer cost from BCA is estimated to be rather small, with the largest loss equivalent to 0.2% of expenditure to the bottom percentile of consumers.

[Figure 11 about here.]

Figure 11 shows the distribution of consumer cost from complementing the 30 USD/t EU carbon price with a BCA. Within countries, I estimate the cost distribution to follow an inverted U-shape—consumers with the highest and lowest incomes are incur the largest cost.

[Figure 12 about here.]

Figure 12 shows the average consumer cost for the 27 EU member countries. Differences between countries are rather small and there is no clear relationship with national income levels.

[Figure 13 about here.]

Figure 13 again shows the distribution of consumer costs in absolute terms. Complementing the EU ETS with a BCA would have resulted in a cost to the median EU consumer of about 20 USD in 2004.

Leakage reduction: This paper contributes to the literature on BCA by providing estimates of its consumer cost incidence. As a byproduct, my model also validates previous findings on the potential for leakage reduction. In the 40 countries covered, total CO_2 emissions in 2004 were 20.4Gt. I estimate that an EU-wide carbon price of 30 USD/t (EU ETS) would have led to a global emissions reduction of 2.2Gt. Complementing the EU-wide price with a BCA would have increased the reduction by about 25% to 2.8Gt. This is in line with the previous literature, which finds significant leakage reduction potential for BCA ¹⁸. The rough estimate of 600 million tons less in CO_2 emissions at a cost of 20 USD for the median EU consumer suggests that the BCA would have led to a net welfare gain for EU consumers. It should be noted that this is before additional gains from tariff revenue, domestic production gains, and climate mitigation benefits to the rest of the world.

¹⁸Studies using rich Computational General Equilibrium models (e.g. Elliott et al., 2010; Böhringer et al., 2016a,b) find that BCA have the potential to significantly reduce carbon leakage and shift the economic burden of emission reduction to countries without domestic carbon prices (Aldy and Pizer, 2015; Böhringer et al., 2018). Aichele and Felbermayr (2015) construct a theoretical gravity model in the vein of Krugman (1980) to model the carbon content of trade. Their model predicts significant leakage in absence of BCA. Larch and Wanner (2017) use an empirical gravity approach and confirm that carbon tariffs somewhat reduce leakage at a global scale while imposing a net welfare loss on representative consumers in developing countries.

5 Robustness

The results reported above rely on a number of model assumptions stated in Section 2 as well as the parameter estimates obtained in Section 3. In this section, I report results from robustness checks which support my confidence in the provided estimates.

5.1 Consistency with Consumption Micro-data (CEX)

My approach follows Fajgelbaum and Khandelwal (2016) in identifying the parameters of a global demand system based on aggregate trade flows between countries. The distribution of consumer demand within countries is extrapolated based on observed differences in aggregate flows between countries¹⁹. Simply put, because richer countries buy more textiles from the United States and fewer textiles from India, I expect richer consumers within countries to buy more textiles from the United States from the United States and fewer textiles from India. This is of course a rather strong assumption.

[Figure 14 about here.]

To test this assumption, I compare the within-country expenditure distribution derived from my model to micro-data from the United States. I focus on the initial incidence of carbon pricing in the United States, which can be thought of as the cost to consumers of introducing a carbon price of 1 USD/t before any demand substitution takes place. Figure 14 compares this estimates of this incidence across the US income distribution in 2004. The red (solid) line shows the cost to US consumers in 2004 estimated by my structural demand model. The blue (dashed) line shows the same measure based on expenditure data from the US Consumer Expenditure Survey (CEX). The CEX reports consumer expenditures on over 600 categories, which I map into the 35 WIOD sectors²⁰. The two different approaches yield highly similar estimates of the distribution of welfare exposure to carbon pricing within the United States.

It is reassuring that the structural estimates from my model match well the patterns based on micro-data for the United States in 2004. Still, I cannot deny the possibility that the demand system I estimate might be a better fit for expenditure patterns in some countries than others.

¹⁹The structural approach used here could be avoided by using a harmonised set of micro-data from all countries describing consumption patterns including the origin of imported goods. I am not aware of any such work. But one steps in such a direction is provided by Rausch et al. (2011), albeit only for one country. They combine a CGE model for the United States with micro-data from the Consumer Expenditure Survey. Their work stresses the importance of accounting for consumer heterogeneity within countries. My framework incorporates a non-homothetic demand system at the global scale and thus represents a further step in that direction.

²⁰Data and methods used to derive the CEX welfare exposure are described in detail in Sager (2017). Both are normalised by dividing through the marginal welfare effect of the average consumer.

5.2 Alternative Input-Output Data (Eora)

The above results are based on parameter values estimated from bilateral trade flows in final goods and inter-industry trade as provided by the World Input-Output Database (WIOD). While it is one of the most commonly used sources for multi-region input-output (MRIO) data, WIOD is subject to a number of limitations. WIOD provides harmonised data on 40 countries and 35 sectors. It covers a significant portion 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 of it. As a consequence, Figures 2, 6 and 10 represent the distributional incidence for about 4.2 of the world population of around 7 billion people.

To check for the robustness of my results, I re-estimate the above incidence based on an alternative MRIO data source—the Eora MRIO database. Eora provides more comprehensive coverage. I use the symmetric and harmonised version of Eora (Eora 26), which covers 189 countries and 26 sectors. The most recent year available is 2015.

[Figure 15 about here.]

Figure 15 compares model estimates using Eora data to those obtained using WIOD. The left panel is equivalent to Figure 2—the incidence of a global carbon price of 30 USD/t in 2004 across the 40 WIOD countries. The right panel shows the same result, but all simulations are based on Eora data instead. Eora covers 189 countries, but the Figure is again limited to the 4.2 billion inhabitants of the 40 countries also included in the WIOD sample. Eora also provides an alternative account of greenhouse gas emissions. I choose emissions accounts, which include six greenhouse gases²¹ emitted from a large range of activities (including land use). The two panels are based on entirely separate estimates of consumer and producer elasticities, industry emissions intensities, and trade flows. Reassuringly, the resulting incidence patterns are highly similar.

Re-estimating the global incidence of carbon pricing using Eora provides a check on the robustness of the above incidence estimates which rely on WIOD. In addition, it makes it possible to estimate the incidence, for all 189 countries—nearly all of the over 7 billion world population—in 2015. I do this in the Appendix.

²¹Specifically, the data includes six Kyoto gases and gas groups as reported in the PRIMAP-hist database: carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), sulphur hexafluoride (SF₆), hydrofluorocarbons(HFCs), and perfluorocarbons (PFCs). Results look qualitatively similar if the analysis is restricted to CO₂ emissions from fossil-fuel combustion as reported by the IEA.

5.3 Alternative Modelling Approaches

Much of the literature estimates the within-country incidence of energy taxes using data from consumer expenditure surveys (Grainger and Kolstad, 2010; Williams et al., 2015, e.g.). These provide detailed micro-data on observed consumer behaviour. We have seen above that my global model matches well the estimates from such an approach, at least for the United States. A first approximation of the incidence can be based on the emissions-intensity of observed consumption. The dotted line in Figure 16 compares my full model to such an approach, ignoring both demand adjustments by consumers and input substitution by producers. This would result in substantial over-estimation of the global consumer cost and its regressivity²².

[Figure 16 about here.]

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 (6) 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 cost²³.

²²The 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)

²³Using Equation (6), the variation in cost to consumers h in countries n can be disaggregated as: $\operatorname{Var}(\hat{\omega}_{n,h}) = \operatorname{Var}(\hat{W}_n) + \operatorname{Var}(\hat{\psi}_h)$.

6 Discussion

I have estimated the global consumer incidence of three carbon pricing scenarios. These estimates focus exclusively 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 two important benefits of carbon pricing-the benefits of using the collected revenue and the benefits of climate mitigation.

First, there may be significant benefits from redistributing revenue collected by any carbon pricing scheme. While the collected revenue from a carbon tax (or a permit auction) can never fully offset the consumer welfare loss due to higher prices, it can be used to significantly alleviate that cost. Importantly, it has been shown in the within-country incidence literature that revenue recycling can alter the incidence of an energy tax (Fullerton, 2011). For example, energy taxes become less regressive if the revenue is used for income tax cuts and may even become progressive when the revenue is used for lump-sum per capita rebates (Rausch et al., 2011)²⁴ or other progressive measures such as food subsidies Gonzalez (2012). In sum, how the revenue of carbon pricing is redistributed can then entirely alter its distributional effect.

Second, 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). The benefit of reducing CO₂ emissions by one unit today—the social cost of carbon (SCC)—is the monetary value of its marginal contribution to future warming and the corresponding damages (for a survey see Tol, 2011). The SCC is notoriously difficult to quantify and subject to large uncertainty (Gillingham et al., 2018). For example, one recent contribution puts the SCC at 31 USD/t (Nordhaus, 2017), another finds a median SCC of 417 USD/t Ricke et al. (2018). Much of expert opinion falls into a range of 80-200 USD/t (Pindyck, 2016). Models that disaggregate the SCC by region tend to find three trends. First, larger damages fall on larger economies (both richer and more populous countries), as climate damage is usually assumed to be proportional to economic output (Burke et al., 2015). Second, damages are larger for countries that have higher temperatures today, and smaller (to sometimes negative) for colder countries (Ricke et al., 2018). Third, there is some evidence that at a given level of baseline temperature, the marginal damage of temperatures to economic output is larger for poorer countries (Dell et al., 2012; Burke et al., 2015). In sum, climate mitigation is likely to disproportionately benefit countries that are simultaneously hot and poor.

[Figure 17 about here.]

²⁴In addition, Rausch et al. (2011) show that changes in relative factor incomes may constitute another progressive element as they lower relative prices of land and capital.

In this paper, I do not attempt to systematically compare the consumer cost of carbon pricing to the benefits of climate mitigation. For illustrative purposes, Figures 17 and 18 show the country-level cost to consumers under a global price of 30 USD per *tCO2e* across 189 countries (using Eora data) in 2015. The simulated price applies to the six Kyoto greenhouse gases and is in addition to existing schemes such as the EU ETS. The average consumer incurs a cost equivalent to 1.7% of her annual budget, for a total of 1.29 trillion USD. Figure 17 shows considerable variation between countries. As discussed above, the relative cost is highest in low-income countries and those relying heavily on fossil fuel inputs. There appears to be then at least some overlap between the countries with the highest consumer cost of carbon pricing and those benefiting most from climate mitigation. Figure 18 shows that the total cost of carbon pricing, just like the SCC, is driven by total output and highest in the large economies, such as China (290bn USD) and the United States (217bn USD).

[Figure 18 about here.]

Overall, I find a regressive consumer cost of carbon pricing schemes—both in the form of a uniform global carbon price and the EU ETS. Meanwhile, the incidence of climate mitigation benefits is likely progressive across countries—with particular benefits to countries that are both hot and poor. These mitigation benefits may weaken or reverse the regressive consumer cost of carbon pricing. I leave a systematic analysis of the net incidence for future work.

The incidence of any carbon pricing scheme will ultimately depend on the use of revenues. This has been found by the within-country incidence literature and it is also what I find in my global incidence analysis. Illustrating this point, the average global consumer cost of 1.7% in Figure 17 falls to 0.2% (162 billion USD) when revenues are subtracted. How the difference of 1.5% is distributed could fully overturn any incidence in consumer cost. My estimates show that the global consumer incidence of carbon pricing is largely driven by between-country differences. This suggests a potentially important role for between-country transfers, either in the form of direct transfers (mentioned in Article 9 of the Paris Agreement) or indirectly by linking domestic climate policies (Mehling et al., 2018).

In conclusion, this paper is the first to estimate how the consumer cost of carbon pricing is distributed globally—both between and within many countries. As any large-scale welfare analysis, my results rely on a number of assumptions and empirical estimates. I have shown that my findings replicate with an alternative data source and match well estimates using more detailed micro-data. I find that the global incidence of carbon pricing is driven by between-country differences, while the cost of Border Adjustments varies more strongly within countries. The results have potentially important implications for the equitable design of global climate policy.



Figure 1: Global price - Global CO₂ emissions

Note: This figure shows global aggregate CO_2 emissions under different levels of a global uniform carbon price per ton of CO_2 simulated in 2004 (40 WIOD countries). Different lines allow for different margins of adjustment in the model: 'No substitution' refers to demand adjustments only with a fixed supply structure; 'input substitution' refers to demand adjustments plus intermediate input substitution by producers; 'input + fuel substitution' refers to the full model allowing for demand adjustments plus intermediate input substitution as well as fuel switching by producers.



Figure 2: Global price of 30 USD/t - Global Distribution of Consumer Cost

Note: This figure shows the global distribution of the consumer cost under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 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 cost is expressed as welfare loss equivalent to losing a 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 model parameters drawn from the joint normal distributions for parameter estimates from estimations (16), (17) and (21).



Figure 3: Global price of 30 USD/t - Within-country Consumer Cost

Note: This figure shows the distribution of the consumer cost in each country under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 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 cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 4: Global price of 30 USD/t - Between-country Consumer Cost

Note: This figure shows the average consumer cost in each country under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries). The horizontal axis shows average per capita levels of expenditure in each of the 40 WIOD countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 5: Global price of 30 USD/t - Global Distribution of Consumer Cost (USD)

Note: This figure shows the global distribution of the consumer cost under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 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 cost is expressed as welfare loss equivalent USD value (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 (16), (17) and (21).



Figure 6: EU price of 30 USD/t - EU Distribution of Consumer Cost

Note: This figure shows the global distribution of the consumer cost under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 490 million inhabitants of the 27 EU countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a 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 model parameters drawn from the joint normal distributions for parameter estimates from estimations (16), (17) and (21).



Figure 7: EU price of 30 USD/t - Within-country Consumer Cost

Note: This figure shows the distribution of the consumer cost in each country under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution within each of the 40 WIOD countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 8: EU price of 30 USD/t - Between-country Consumer Cost

Note: This figure shows the average consumer cost in each country under an EU-wide (27 countries) carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows average per capita levels of expenditure in each of the 40 WIOD countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 9: EU price of 30 USD/t - EU Distribution of Consumer Cost (USD)

Note: This figure shows the global distribution of the consumer cost under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 490 million inhabitants of the 27 EU countries in 2004. The consumer cost is expressed as welfare loss equivalent USD value (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 (16), (17) and (21).





Note: This figure shows the global distribution of the consumer cost under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 490 million inhabitants of the 27 EU countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a 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 model parameters drawn from the joint normal distributions for parameter estimates from estimations (16), (17) and (21).



Figure 11: EU Border Adjustment of 30 USD/t - Within-country Consumer Cost

Note: This figure shows the distribution of the consumer cost in each country under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution within each of the 40 WIOD countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 12: EU Border Adjustment of 30 USD/t - Between-country Consumer Cost

Note: This figure shows the average consumer cost in each country under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows average per capita levels of expenditure in each of the 40 WIOD countries in 2004. The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.



Figure 13: EU BCA of 30 USD/t - EU Distribution of Consumer Cost (USD)

Note: This figure shows the global distribution of the consumer cost under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 490 million inhabitants of the 27 EU countries in 2004. The consumer cost is expressed as welfare loss equivalent USD value (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 (16), (17) and (21).



Figure 14: Comparison of Model Fit to Micro-data - Marginal Incidence

Note: This figure compares the fit of the demand system (this paper) with empirical estimates of the CO_2 intensity of consumption at different income levels in the United States in 2004. The latter are based on household consumption data from the Consumer Expenditure Survey (matched to emissions in Sager, 2017). The horizontal axis shows income deciles of the US expenditure distribution. The vertical axis shows the relative exposure of consumers in each decile to the first marginal USD of carbon pricing (equivalent to the emissions intensity of consumption in t/USD), as a ratio to the average.





Note: This figure compares simulation results using WIOD data (used throughout this paper) to simulation results using the Eora input-output database. Both show the simulated consumer cost under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004. The WIOD results [left axis] are the same as shown in Figure 2. The Eora results [right axis] are based on newly estimated model parameters and new input-output data. The Eora results shown for the subset of 40 countries in WIOD, but estimates with a price applying to all 189 Eora countries and all greenhouse gases (Kyoto classification) emitted from a large range of activities (including land use). The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget. 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 (16), (17) and (21).



Figure 16: Comparison of Global Incidence Estimates by Modelling Choice

Note: This figure shows the global distribution of the consumer cost under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries). The 'full model' replicates the results shown in Figure 2. The 'representative consumer' estimates are from a model that ignores the within-country distribution of incomes. The 'extrapolated' estimates are those from a naive model which calculates the consumer cost 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 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 cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget.

Figure 17: Global price of 30 USD/t in 2015 - Country Average Consumer Cost



Note: This figure shows the country-level average consumer cost under a global uniform price of 30 USD per ton of greenhouse gas emissions (CO_2e) simulated in 2015 (189 Eora countries). Latest data on quality-adjusted prices is from 2011. The simulated price is in addition to any existing carbon pricing scheme in 2015 and applies to six greenhouse gases (Kyoto classification) emitted from a large range of activities (including land use). The consumer cost is expressed as average welfare loss equivalent to losing a share of the total expenditure budget.

Figure 18: Global price of 30 USD/t in 2015 - Country Total Consumer Cost



Note: This figure shows the country-level total consumer cost under a global uniform price of 30 USD per ton of greenhouse gas emissions (CO_2e) simulated in 2015 (189 Eora countries). Latest available data on income and population (Penn World Tables) is from 2014. Latest data on quality-adjusted prices is from 2011. The simulated price is in addition to any existing carbon pricing scheme in 2015 and applies to six greenhouse gases (Kyoto classification) emitted from a large range of activities (including land use). The consumer cost is expressed as country aggregate welfare loss equivalent USD value.

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A1: Derivation of Proposition 1

We consider the change in the log of indirect utility of consumer *h* due to infinitesimal changes in log prices $\{p_j\}_{j=1}^J$ and the log of expenditure \hat{x}_h . Fajgelbaum and Khandelwal (2016) show that the change in indirect utility is:

$$\hat{v}_h = \sum_{j=1}^J \frac{\partial \log v(x_h, \mathbf{p})}{\partial \log p_j} \hat{p}_j + \frac{\partial \log v(x_h, \mathbf{p})}{\partial \log x_h} \hat{x}_h$$
(22)

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:

$$\hat{v}_h = \sum_{j=1}^J \frac{\partial \log v(x_h, \mathbf{p})}{\partial \log x_h} \hat{\omega}_h$$
(23)

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

$$\hat{\omega}_{h} = \sum_{j=1}^{J} (-\hat{p}_{j}) s_{j,h} + \hat{x}_{h}$$

$$= \sum_{j=1}^{J} (-\hat{p}_{j}) S_{j} + \sum_{j=1}^{J} (-\hat{p}_{j}) (s_{j,h} - S_{j}) + \hat{x}_{h}$$

$$= \hat{W} + \hat{\psi}_{h} + \hat{x}_{h}$$
(24)

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 described above, 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:

$$\hat{\psi}_h = -\left(\sum_{j=1}^J \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) \tag{25}$$

This finally gives the welfare change of consumer *h* as:

$$\hat{\omega}_{h} = \hat{W} - \left(\sum_{j=1}^{J} \beta_{j} \hat{p}_{j}\right) \log\left(\frac{x_{h}}{\tilde{x}}\right) + \hat{x}_{h}$$
(26)

A2: Derivation of Proposition 3

Given the assumed initial price changes to $p_j^{new} = (1 + \tau \varepsilon_j)p_j$, the new share of inputs *j* in the expenditure of sector *k* would become:

$$S_{jk}^{new} = \frac{(1 + \tau \varepsilon_j) p_j f_{jk}}{P_k^{new} X_k} = T_k^{(\sigma_k - 1)} a_{jk} p_j^{(1 - \sigma_k)} (1 + \tau \varepsilon_j)^{(1 - \sigma_k)} (P_k^{new})^{\sigma_k - 1}$$
(27)

The relation to the previous expenditure share on intermediate input *j* is:

$$\frac{S_{jk}^{new}}{S_{jk}} = (1 + \tau \varepsilon_j)^{(1 - \sigma_k)} \left(\frac{P_k^{new}}{P_k}\right)^{\sigma_k - 1}$$
(28)

But of course, these adjustments to input use will themselves change the structure of supply chains and, in consequence, the emissions intensities ε_k . We now can express an updated version of the 'Direct Requirement Matrix' \mathbf{C}^{new} which has elements:

$$c_{jk}^{new} = S_{jk}^{new} \frac{P_k^{new}}{1 + \tau\varepsilon_j} = \left(\frac{P_k^{new}}{1 + \tau\varepsilon_j}\right)^{\sigma_k} c_{jk}$$
(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_{jk} which characterised the dollar value of input required from sector j to produce one dollar value of final output in sector k.

Let us now define a new unit of measurement for each sector k, which we shall call 'previous dollar value unit' (PDU). One PDU is equal to the amount of good k that could be bought at the original prices (we assume throughout that prices of good j used as intermediate inputs are the same as when j is bought as final good). 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 k we require c_{jk}^{new} units (in PDU) of intermediate good j. Essentially, I normalise all initial prices to $p_j = 1 \forall j$, which also implies that P = 1. This works because only relative price changes matter.

The 'direct emissions intensity' $\delta_j^{new} = \delta_j$ remains unchanged in this step but now also characterises the direct emissions per PDU output (i.e. the emissions related to the value-added for one unit produced). Calculating new 'total emissions intensities' per PDU should then be $\mathbf{e}^{new} = (I - \mathbf{C}^{new})^{-1}\mathbf{d}$ and the final goods price of *j* including the carbon price is $1 + \tau \varepsilon_j^{new}$.

A3: Numerical approximation of new equilibrium production

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

- 1. Calculate initial adjustment of production $\{A_{ji}^{new}\}$ when carbon price is levied on emissions intensities $\{\varepsilon_j\}$ based on original production $\{A_{ji}\}$
- 2. Calculate emissions intensities $\{\varepsilon_i^{new}\}$ based on adjusted production $\{A_{ii}^{new}\}$
- 3. Use new $\{\varepsilon_{j}^{new}\}$ to calculate further adjustment in production $\{A_{ji}^{new_2}\}$
- 4. Re-calculate $\{\varepsilon_{j}^{new_2}\}$ based on adjusted production $\{A_{ji}^{new_2}\}$
- 5. Back to step 1.

In all simulations, the procedure converges very quickly to a state where additional rounds of adjustment are negligible.

A4: Parameter Robustness

Table 2:	Average	estimate of				
	income	semi-elasticity				
	by countr	y				
Country	Beta	Country	Beta			
AUS	0.017	IRL	0.000			
AUT	0.002	ITA	0.009			
BEL	-0.019	JPN	0.039			
BGR	-0.006	KOR	0.007			
BRA	-0.016	LTU	0.000			
CAN	-0.007	LUX	-0.011			
CHN	-0.005	LVA	0.000			
CYP	0.013	MEX	-0.019			
CZE	-0.006	MLT	0.004			
DEU	-0.003	NLD	-0.007			
DNK	0.002	POL	-0.003			
ESP	0.003	PRT	-0.004			
EST	0.001	ROM	-0.004			
FIN	0.008	RUS	-0.005			
FRA	-0.004	SVK	-0.003			
GBR	0.014	SVN	-0.002			
GRC	0.013	SWE	0.002			
HUN	0.001	TUR	-0.001			
IDN	-0.026	TWN	0.016			
IND	-0.031	USA	0.097			

Note.-Average estimates of the income (semi)-elasticities as estimated from (16) and (17) for the WIOD cross-section 2004. Country averages across the 35 supply sectors each.

	WIOD Sector	Beta	Gamma
1	Agriculture, Hunting, Forestry and Fishing	-0.022	0.007
2	Mining and Quarrying	0.000	0.001
3	Food, Beverages and Tobacco	-0.016	0.015
4	Textiles and Textile Products	-0.004	0.002
5	Leather, Leather and Footwear	-0.001	0.001
6	Wood and Products of Wood and Cork	0.000	0.000
7	Pulp, Paper, Paper, Printing and Publishing	0.002	0.002
8	Coke, Refined Petroleum and Nuclear Fuel	0.000	0.003
9	Chemicals and Chemical Products	-0.001	0.003
10	Rubber and Plastics	0.000	0.001
11	Other Non-Metallic Mineral	0.000	0.001
12	Basic Metals and Fabricated Metal	0.000	0.002
13	Machinery, Nec	-0.005	0.005
14	Electrical and Optical Equipment	-0.004	0.005
15	Transport Equipment	-0.003	0.006
16	Manufacturing, Nec; Recycling	0.001	0.002
17	Electricity, Gas and Water Supply	0.000	0.006
18	Construction	-0.014	0.041
19	Sale, Mntnce and Repair Motor Veh.; Retail Sale of Fuel	0.003	0.004
20	Wholesale Trade and Commission Trade, Except of Motor Veh.	0.001	0.015
21	Retail Trade, Except of Motor Veh.; Repair of Household Goods	0.001	0.017
22	Hotels and Restaurants	0.006	0.014
23	Inland Transport	-0.008	0.006
24	Water Transport	-0.001	0.000
25	Air Transport	0.000	0.001
26	Other Supporting and Aux. Transport Activities; Travel Agencies	0.002	0.002
27	Post and Telecommunications	0.000	0.006
28	Financial Intermediation	0.006	0.013
29	Real Estate Activities	0.015	0.031
30	Renting of M&Eq and Other Business Activities	0.003	0.008
31	Public Admin and Defence; Compulsory Social Security	0.007	0.040
32	Education	0.004	0.015
33	Health and Social Work	0.022	0.026
34	Other Community, Social and Personal Services	0.004	0.016
35	Private Households with Employed Persons	0.001	0.001

 Table 3: Average estimate income and price elasticities by sector

 WIOD Sector
 Beta
 Ga

Note.-Average estimates of the income (semi)-elasticities and price elasticities as estimated from (16) and (17) for the WIOD cross-section 2004. Sector averages across the 40 origin countries each.

			5	1					
2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
1.00	0.97	0.98	0.96	0.92	0.89	0.82	0.69	0.58	0.66
0.97	1.00	0.96	0.94	0.92	0.88	0.81	0.69	0.58	0.64
0.98	0.96	1.00	0.99	0.96	0.93	0.88	0.77	0.67	0.73
0.96	0.94	0.99	1.00	0.99	0.97	0.93	0.84	0.75	0.80
0.92	0.92	0.96	0.99	1.00	0.99	0.97	0.90	0.82	0.85
0.89	0.88	0.93	0.97	0.99	1.00	0.99	0.93	0.86	0.89
0.82	0.81	0.88	0.93	0.97	0.99	1.00	0.97	0.92	0.93
0.69	0.69	0.77	0.84	0.90	0.93	0.97	1.00	0.98	0.97
0.58	0.58	0.67	0.75	0.82	0.86	0.92	0.98	1.00	0.97
0.66	0.64	0.73	0.80	0.85	0.89	0.93	0.97	0.97	1.00
	2000 1.00 0.97 0.98 0.96 0.92 0.89 0.89 0.82 0.69 0.58 0.66	2000 2001 1.00 0.97 0.97 1.00 0.98 0.96 0.96 0.94 0.92 0.92 0.89 0.88 0.82 0.81 0.69 0.69 0.58 0.58 0.66 0.64	2000 2001 2002 1.00 0.97 0.98 0.97 1.00 0.96 0.98 0.96 1.00 0.98 0.96 1.00 0.96 0.94 0.99 0.92 0.92 0.96 0.89 0.88 0.93 0.82 0.81 0.88 0.69 0.69 0.77 0.58 0.58 0.67 0.66 0.64 0.73	2000 2001 2002 2003 1.00 0.97 0.98 0.96 0.97 1.00 0.96 0.94 0.98 0.96 1.00 0.99 0.96 0.94 0.99 1.00 0.92 0.92 0.96 0.99 0.89 0.88 0.93 0.97 0.82 0.81 0.88 0.93 0.69 0.69 0.77 0.84 0.58 0.58 0.67 0.75 0.66 0.64 0.73 0.80	2000 2001 2002 2003 2004 1.00 0.97 0.98 0.96 0.92 0.97 1.00 0.96 0.94 0.92 0.97 1.00 0.96 0.94 0.92 0.98 0.96 1.00 0.99 0.96 0.96 0.94 0.99 1.00 0.99 0.92 0.92 0.96 0.99 1.00 0.89 0.88 0.93 0.97 0.99 0.82 0.81 0.88 0.93 0.97 0.69 0.69 0.77 0.84 0.90 0.58 0.58 0.67 0.75 0.82 0.66 0.64 0.73 0.80 0.85	2000 2001 2002 2003 2004 2005 1.00 0.97 0.98 0.96 0.92 0.89 0.97 1.00 0.96 0.94 0.92 0.88 0.98 0.96 1.00 0.99 0.96 0.93 0.96 0.94 0.99 1.00 0.99 0.97 0.96 0.94 0.99 1.00 0.99 0.97 0.92 0.92 0.96 0.99 0.96 0.93 0.96 0.94 0.99 1.00 0.99 0.97 0.92 0.92 0.96 0.99 1.00 0.99 0.89 0.88 0.93 0.97 0.99 1.00 0.82 0.81 0.88 0.93 0.97 0.99 0.69 0.69 0.77 0.84 0.90 0.93 0.58 0.58 0.67 0.75 0.82 0.86 0.66 0.64 0.73	2000 2001 2002 2003 2004 2005 2006 1.00 0.97 0.98 0.96 0.92 0.89 0.82 0.97 1.00 0.96 0.94 0.92 0.88 0.81 0.98 0.96 1.00 0.99 0.96 0.93 0.88 0.96 0.94 0.99 1.00 0.99 0.97 0.93 0.96 0.94 0.99 1.00 0.99 0.97 0.93 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.93 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.93 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.89 0.88 0.93 0.97 0.99 1.00 0.99 0.82 0.81 0.88 0.93 0.97 0.99 1.00 0.69 0.69 0.77 0.84	2000 2001 2002 2003 2004 2005 2006 2007 1.00 0.97 0.98 0.96 0.92 0.89 0.82 0.69 0.97 1.00 0.96 0.94 0.92 0.88 0.81 0.69 0.97 1.00 0.96 0.94 0.92 0.88 0.81 0.69 0.98 0.96 1.00 0.99 0.96 0.93 0.88 0.77 0.96 0.94 0.99 1.00 0.99 0.97 0.93 0.84 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.93 0.84 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.90 0.89 0.88 0.93 0.97 0.99 1.00 0.97 0.90 0.89 0.88 0.93 0.97 0.99 1.00 0.97 0.69 0.69 0.77 0.84 <th>2000 2001 2002 2003 2004 2005 2006 2007 2008 1.00 0.97 0.98 0.96 0.92 0.89 0.82 0.69 0.58 0.97 1.00 0.96 0.94 0.92 0.88 0.81 0.69 0.58 0.98 0.96 1.00 0.99 0.96 0.93 0.88 0.77 0.67 0.96 0.94 0.99 0.96 0.93 0.88 0.77 0.67 0.96 0.94 0.99 1.00 0.99 0.97 0.93 0.84 0.75 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.90 0.82 0.89 0.88 0.93 0.97 0.99 1.00 0.99 0.93 0.86 0.82 0.81 0.88 0.93 0.97 0.99 1.00 0.97 0.92 0.69 0.69 0.77 0.84 0.90</th>	2000 2001 2002 2003 2004 2005 2006 2007 2008 1.00 0.97 0.98 0.96 0.92 0.89 0.82 0.69 0.58 0.97 1.00 0.96 0.94 0.92 0.88 0.81 0.69 0.58 0.98 0.96 1.00 0.99 0.96 0.93 0.88 0.77 0.67 0.96 0.94 0.99 0.96 0.93 0.88 0.77 0.67 0.96 0.94 0.99 1.00 0.99 0.97 0.93 0.84 0.75 0.92 0.92 0.96 0.99 1.00 0.99 0.97 0.90 0.82 0.89 0.88 0.93 0.97 0.99 1.00 0.99 0.93 0.86 0.82 0.81 0.88 0.93 0.97 0.99 1.00 0.97 0.92 0.69 0.69 0.77 0.84 0.90

Table 4: Consistency of parameter estimates - Beta

Note.-Pairwise correlations between 1400 income (semi)-elasticities as estimated from (16) and (17) for two yearly cross-sections of WIOD.

Table 5: Consistency of parameter estimates - Gamma

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

Note.-Pairwise correlations between 35 price elasticity parameters as estimated from (16) for two yearly cross-sections of WIOD.

				2	1				U	
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
2000	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2001	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2002	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.98
2003	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99
2004	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
2005	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2006	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	0.99
2007	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00
2008	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00
2009	0.98	0.98	0.98	0.99	0.99	1.00	0.99	1.00	1.00	1.00

Table 6: Consistency of parameter estimates - Sigma

Note.-Pairwise correlations between 35 CES elasticities as estimated from (21) for two yearly cross-sections of WIOD.

A5: Alternative Carbon Price of 100 USD/t in 2004



Figure 19: Global price of 100 USD/t - Global Distribution of Consumer Cost

Note: Same as Figure 2 but with a global uniform carbon price of 100 USD per ton of CO_2 simulated in 2004 (40 WIOD countries).

Figure 20: EU price of 100 USD/t - EU Distribution of Consumer Cost



Note: Same as Figure 6 but with an EU-wide (27 countries) uniform carbon price of 100 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries).

Figure 21: EU Border Adjustment of 100 USD/t - EU Distribution of Consumer Cost



Note: Same as Figure 10 but with a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 100 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries).

A6: Carbon Price of 30 USD/t - 189 Countries (Eora) - 2015



Figure 22: Global price of 30 USD/t - Global Distribution of Consumer Cost

Note: This figure shows the global distribution of the consumer cost under a global uniform price of 30 USD per ton of greenhouse gas emissions (CO_2e) simulated in 2015 (189 Eora countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 7.2 billion inhabitants of the 189 Eora countries in 2015. The price is applied to all 189 Eora countries and all greenhouse gases (Kyoto classification) emitted from a large range of activities (including land use). The consumer cost is expressed as welfare loss equivalent to losing a share of the total expenditure budget. 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 (16), (17) and (21).