The London School of Economics and Political Science

Inequality, Consumer Choice, and the Environment

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated otherwise.

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Abstract

In this thesis I investigate the relationship between income inequality and the carbon content of consumption, as well as the repercussions this relationship has for policies intended to lower emissions and soften inequalities.

In Chapter 1 I show that the consumer cost of carbon pricing is globally regressive, and more so across countries than within. I show this using a novel, global approach to estimating the consumer cost. 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 trade data. I also estimate the incidence of the EU Emissions Trading System introduced in 2005 and a hypothetical EU Border Carbon Adjustment.

In Chapter 2 I show how the distribution of income may influence aggregate emissions. I quantify the carbon dioxide (CO_2) content of household consumption using micro-data from the United States. I estimate Environmental Engel curves, which describe the relationship between household income and CO_2. I then describe a potential "equity-pollution dilemma"—progressive income redistribution may raise aggregate emissions. I estimate that progressive transfers may raise household carbon by 5.1% at the margin, and by 2.3% under complete redistribution.

In Chapter 3 I ask how the inequality-consumption relationship changes when consumers are motivated by status. I propose a model in which consumption is influenced by a reference level shaped by peer consumption. While status-seeking complicates comparative statics, I show that the sign of the inequality-consumption relationship can be predicted under certain conditions. In particular, status-seeking acts like a multiplier when the reference level is a simple mean. Concave Engel curves suggest that more inequality lowers demand for status goods, which also tend to be more carbon intensive.

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Introduction

Economic inequality and climate change are high on policy agendas around the world. In this thesis I investigate the relationship between the two. This relationship can work in both directions. On the one hand, environmental policy can have distributional effects. These are frequently studied by economists, with a large body of work on the distributional effects of environmental policy across income levels, usually within a single country. On the other hand, the degree of inequality in a society may also affect environmental outcomes. This direction of the relationship—from inequality to environmental outcomes—has received far less attention. I investigate both channels in this thesis, which is comprised of three chapters. In each chapter I focus on a different aspect of the inequality-environment relationship.

In Chapter 1 I focus on the distributional effects of pricing carbon dioxide emissions. Carbon pricing—most common in the form of a carbon tax or permit trading scheme—is becoming an increasingly popular policy instrument to address the global climate externality. 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. I focus on this consumer cost, before any potential revenue transfers are made, and base my analysis on consumption patterns at different income levels and in different countries. I thus contribute to a large literature concerned with how the cost of carbon (and energy) taxes is distributed. This literature has largely focused on the distributional effects of these policies across consumers within mostly rich countries (Poterba, 1991; Grainger and Kolstad, 2010; Williams et al., 2015). I estimate for the first time how the consumer cost of carbon pricing is distributed globally—both between countries and across income levels within them.

To do so, 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 in final goods. On the supply side, I model substitution of intermediate inputs along global value chains. I estimate all model parameters from data on bilateral trade flows and then simulate the global consumer incidence of three carbon pricing scenarios. I find that the consumer cost of a global uniform carbon price would be highly regressive—with a relative cost to consumers in the bottom half of the world income distribution twice as large as the cost to 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. Similar to the global carbon price, I find that the EU Emissions Trading System (ETS) introduced in 2005 was likely regressive across the 490 million European consumers and that this incidence is again driven by between-country differences—consumers in Eastern European and Baltic EU states are most affected. Finally, I investigate the consumer cost of introducing Border Carbon Adjustments (BCA). These are carbon prices targeted at traded goods when one economy has a domestic carbon price while its trading partners don't. I find that complementing an EU-wide carbon price with a BCA would most affect the poorest and richest EU consumers. This time, the within-country variation in consumer cost dominates that between countries. Beyond the results for specific scenarios, the chapter contributes to the literature by proposing a novel framework to estimate the consumer cost incidence of carbon pricing globally.

In Chapters 2 and 3 I focus on the other direction of the inequality-environment relationship—the possible consequences of income inequality for environmental outcomes. This link is far less studied, but may have important implications for the design of redistributive policies. This is particularly relevant in the context of the rising inequality levels documented in many rich countries since the 1970s (e.g. Atkinson et al., 2011). Both the continued growth of inequality and the policies intended to redistribute income may have significant environmental side effects. I turn to this relationship in Chapter 2, asking what the consequences of income redistribution for aggregate emissions may be. I again focus on the demand side of the economy. Using microdata on consumption patterns in the United States, I link the annual expenditures of households to their carbon dioxide (CO_2) emissions content. I do so using methods of input-output based emissions accounting. I then estimate Environmental Engel curves (EECs), which represent household carbon across different levels of income. Just like EECs for air pollutants (estimated in Levinson and O'Brien, 2019), I find EECs for CO_2 to be upward-sloping and concave. This implies that embedded CO_2 is a normal good (income elasticity above 0) that behaves like a necessity (income elasticity below 1). I also find that EECs are shifting downwards over time—each level of income is linked to less CO_2 in later years, mostly due to reductions in the emissions intensity of consumption.

Given the key role of income in shaping household carbon, I then consider the consequences of income redistribution for consumption patterns and emissions. Based on the observation of concave EECs, I formulate and quantify what I call the "equity-pollution dilemma"—positive income redistribution may raise aggregate demand for carbon emissions. Following the initial formulation of the dilemma by Scruggs (1998), previous contributions focused mostly on empirical association studies using cross-country analyses following Heerink et al. (2001). As a key contribution, I quantify the dilemma using micro-data on household consumption within a single country. Based on a quadratic specification of EECs, I find a simple formula for the "equity-pollution dilemma" as a function of the curvature of EECs and Gini's mean difference income dispersion measure. For the United States in 2009, I predict that income transfers would have raised household carbon by 5.1% at the margin and by about 2.3% under complete income redistribution. The "equity-pollution dilemma" is larger for CO_2 than for methane (CH_4) and nitrous oxide (N_2O).

The above "equity-pollution dilemma" holds when consumer preferences are accurately described by EECs. Importantly, it presupposes that the demand of consumers at a given income level is not influenced by the income distribution itself. Recent contributions have highlighted one dynamic which may violate this exogeneity assumption—the desire of consumers for status. The choice of each consumer may be influenced by the observed consumption levels of others. This suggests that the distribution of income will not only shape aggregate demand via changes to individual budgets, but also via peer effects between consumers. The shape of Engel curves changes in step with the income distribution. An "equity-pollution dilemma" suggested by the initial shape of Engel curves may then not hold when considering these knock-on effects. In Chapter 3 I investigate the conditions under which we can still speak of a systematic relationship between inequality and consumption, despite status-seeking consumption. To facilitate the analysis, I propose a formulation of status-seeking based on a consumption reference level. The proposed formulation of status-seeking is general enough to encompass a number of more ad-hoc models proposed in previous contributions (e.g. Dupor and Liu, 2003; Bowles and Park, 2005).

I then assess how changes in the distribution of income may impact aggregate demand for positional goods in the presence of status-seeking. In particular, I ask if and under what conditions aggregate positional consumption responds in a predictable fashion to any mean-preserving income transfer. These are the conditions under which we may reasonably claim a systematic relationship between the degree of income inequality and the degree of status-seeking consumption in a society. I show that when the reference level is the simple mean of positional consumption, status-seeking will amplify the comparative statics implied by the curvature of static Engel curves (at a given equilibrium reference level). Put differently, status-seeking then works like a multiplier effect. Combining household expenditure data from the United States with measures of the "visibility" of different goods (from Heffetz, 2011), I find that Engel curves for visible goods are concave—suggesting that more income inequality results in less aggregate demand for these goods. In addition, I find that these goods also appear to be relatively more carbon intensive. When the reference level is instead a weighted mean, giving differentiated weight to the positional consumption levels of different consumers, a reversal of implied comparative statics is possible.

Each chapter contributes something new to the academic literature—both on a conceptual and on a methodological level. Chapter 1 expands the consumer incidence analysis of carbon pricing, which so far mostly focused on individual countries, to the global scale. It achieves this by adopting methods from the trade literature, using structural gravity equations to identify relevant model parameters from aggregate trade flows. Explicitly modelling trade flows also enables me to estimate the distributional incidence of BCA targeted at traded goods for the first time. Meanwhile, Chapter 2 provides micro-level evidence on a topic that has mostly been studied at the macro-scale—the relationship between income inequality and carbon emissions. Based on quadratic EECs, it presents a simple way of quantifying the "equity-pollution dilemma". Finally, Chapter 3 contributes to the understanding of the interplay between status-seeking consumer preferences and income inequality. While previous analyses of status-seeking have mostly focused on average effects in signalling models of status, Chapter 3 presents an analysis of distributional comparative statics in a model of status-seeking based on a reference level. In both Chapters 2 and 3, Engel curves estimated from household-level consumption data serve to bridge the gap between theory and observed behaviour.

In addition to its academic contribution, this thesis may also inform the policy debates on income inequality and climate change. Each chapter links these two phenomena and shows how policies that are targeted at one of them—either inequality or emissions—may trigger undesirable consequences for the other. Chapter 1 shows that carbon pricing may disproportionately affect lower income consumers around the world, at least before considering the use of collected revenue and the benefits of reduced climate damage. Meanwhile, Chapters 2 and 3 show that progressive income redistribution may inadvertently raise consumer demand for embedded emissions—both by shifting demand towards carbon intensive necessities and by intensifying status competition. Taken as a whole this thesis thus highlights the importance of considering the combined effects of policies targeted at limiting greenhouse gas emissions and reducing economic inequality.

Chapter 1

The Global Consumer Incidence of Carbon Pricing: Evidence from Trade

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. Similar 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 an EU-wide carbon price follows an inverted U-shape—the richest and the poorest consumers in the EU incur the largest cost.

1.1 Introduction

Governments around the world are introducing prices on carbon dioxide (CO_2) emissions. In 2005, when the European Union launched its Emissions Trading Scheme (ETS), less than 5% of global greenhouse gas emissions were subject to a price. In 2020, price coverage will exceed 20% with the launch of China's permit scheme (World Bank and Ecofys, 2018). A price on carbon emissions 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 chapter, 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 approach complements research on other channels that shape the global welfare effects of climate policy. Importantly, we may wish to compare the cost of carbon pricing to the benefits of reduced climate damage. Recent evidence suggests that these benefits vary significantly across regions and may fall disproportionately to poor countries with high average temperatures (Burke et al., 2015; Nordhaus, 2017). By estimating how the consumer cost of carbon pricing is distributed globally, I contribute another element towards a more complete welfare analysis 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 is 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 an EU-wide carbon price 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 chapter 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 chapter 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 chapter 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 chapter 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 chapter then contributes to the literature by providing the first estimate of the consumer incidence of BCA to complement an EU-wide carbon price.

Third, this chapter adds to a growing literature applying structural gravity approaches to environmental policy analysis. For example, Shapiro (2016) uses such an approach to characterise the CO_2 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 CO_2-content of aggregate consumption. In this chapter, 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.

The rest of this chapter proceeds as follows. Section 1.2 introduces the structural model of the global economy and Section 1.3 shows how I estimate the relevant model parameters from trade data. Section 1.4 presents the main results and Section 1.5 contains robustness checks. Section 1.6 concludes with a discussion.

1.2 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.

1.2.1 Demand: A global Almost Ideal 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[1].

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 (PIGLOG) preferences proposed by Muellbauer (1975), where indirect utility takes the form:*

$$v(x_h, \mathbf{p}) = F\left[\left(\frac{x_h}{a(\mathbf{p})}\right)^{\frac{1}{b(\mathbf{p})}}\right] \tag{1.1}$$

We further assume that $F(.)$ is an increasing and well-behaved function and that the price aggregators have the following properties:

$$a(\mathbf{p}) = \exp\left(\underline{\alpha} + \sum_{j=1}^{J} \alpha_j \log p_j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{J} \gamma_{jk} \log p_j \log p_k\right) \tag{1.2}$$

$$b(\mathbf{p}) = \exp\left(\sum_{j=1}^{J} \beta_j \log p_j\right) \tag{1.3}$$

[1]Where possible, I stay close to the notation used in Fajgelbaum and Khandelwal (2016), whose empirical strategy I follow to estimate the demand parameters.

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[2].

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

$$s_j(\mathbf{p}, x_h) = \frac{x_{jh}}{x_h} = \alpha_j + \sum_{k=1}^{J} \gamma_{jk} \log p_k + \beta_j \log\left(\frac{x_h}{a(\mathbf{p})}\right) \tag{1.4}$$

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:

$$S_j = \alpha_j + \sum_{k=1}^{J} \gamma_{jk} \log p_k + \beta_j y \tag{1.5}$$

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 $\sum$ is the Theil index of the income distribution[3].

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 1.3. 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 (α_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.

[2]In the words of Deaton and Muellbauer (1980), $a(\mathbf{p})$ is the cost of "subsistence" and $b(\mathbf{p})$ the relative cost of "bliss".

[3]The 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:*

$$\begin{aligned} \hat{\omega}_h &= \sum_{s=1}^{S} (-\hat{p}_j)\, S_j &- \left(\sum_{s=1}^{S} \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) &\quad +\hat{x}_h \\ &= \hat{W} &+ \hat{\psi}_h &\quad +0 \end{aligned} \tag{1.6}$$

Proof. See Appendix 1, 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 change in (log) income of h. I assume throughout that carbon pricing does not change incomes ($\hat{x}_h = 0$)[4]. For non-marginal changes in prices $\hat{\mathbf{p}}$, equation (1.6) 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 (so 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 chapter. A non-homothetic gravity approach has previously been applied to the analysis of the CO_2 content of consumption by Caron and Fally (2018). They study how countries' per capita income levels relate to aggregate energy demand and CO_2 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.

[4]There 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.

1.2.2 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:*

$$min\ C_k = \sum_j \phi_{jk} f_{jk} \quad s.t.\ T_k \left(\sum_j a_{jk}^{1/\sigma_k} f_{jk}^{(\sigma_k-1)/\sigma_k} \right)^{\sigma_k/(\sigma_k-1)} = X_k \tag{1.7}$$

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:

$$S_{jk} = \frac{\phi_{jk} f_{jk}}{C_k} = a_{jk} \phi_{jk}^{(1-\sigma_k)} P_k^{(\sigma_k-1)} \tag{1.8}$$

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 $\times$ 35 sectors) sectors. These come from the World Input-Output Database (WIOD), which is one of the most commonly used multi-regional input-output (MRIO) databases[5]. Once elasticities are estimated, I can simulate input

[5]One limitation of using WIOD data is that I cover only 35 sectors of the economy. As such, I will

substitution dynamics and approximate the resulting equilibrium input-output structure of the economy. 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)[6]. 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).

1.2.3 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 emissions accounting, which I use to estimate changes in final goods prices. As I discuss in Chapter 2, these methods are frequently used to characterise the indirect emissions embodied in consumption (e.g. Sager, 2017; Levinson and O'Brien, 2019). 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:

$$\mathbf{x} = \mathbf{C}\mathbf{x} + \mathbf{y} \tag{1.9}$$

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.

[6]Shapiro (2016) applies a structural gravity approach to model the CO_2 content of transportation—both international and intranational. He finds that the global gains from trade vastly exceed the costs due to CO_2 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, $\mathbf{x}$ is the K-vector of aggregate outputs in value terms (elements $p_k X_k$), $\mathbf{C}$ is the $(K \times K)$-matrix of normalised input requirements c_{jk} and $\mathbf{y}$ 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 instead of volume. In a prominent example, Acemoglu et al. (2012b) use such a linear mapping to describe the network structure of an economy with Cobb-Douglas technologies[7].

The Direct Requirement matrix $\mathbf{C}$ 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 $\mathbf{T}$:

$$\mathbf{x} = [\mathbf{I} - \mathbf{C}]^{-1} \mathbf{y} = \mathbf{T}\mathbf{y} \tag{1.10}$$

Elements of $\mathbf{T}$, 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 $\mathbf{d}$ of direct emissions intensities δ_j describes for each sector the CO_2 emissions per dollar output. It translates into total emissions as follows:

$$\mathbf{e} = \mathbf{T}'\mathbf{d} \tag{1.11}$$

Element ε_k of $\mathbf{e}$ then summarises the total CO_2 emissions intensity (tons of CO_2 per \$) 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. When evaluating carbon pricing scenarios, I simulate a new equilibrium input-output structure of the economy ($\mathbf{C}$ and $\mathbf{T}$), which yields a new set of emissions intensities ($\mathbf{e}$). These directly translate into final price changes seen by consumers.

[7]When technologies are of the Cobb-Douglas variety, C is constant for all price combinations (as in Acemoglu et al., 2012b, and others). I add further flexibility in input substitution by 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 A.3.

1.2.4 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 CO_2 emissions. When no input substitution takes place, this takes the following form[8].

Proposition 2 (Price effect without substitution) *Assume a carbon price τ (in \$ per ton of CO_2) is introduced. Holding constant the structure of value chains* $\mathbf{C}$ *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 (following Leontief, 1970). 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:*

$$c_{jk}^{new} = c_{jk}\left(\frac{\left(\sum_i a_i(1+\tau_{ik}\varepsilon_i^{new})^{(1-\sigma_k)}\right)^{1/(1-\sigma_k)}}{1+\tau_{jk}\varepsilon_j^{new}}\right)^{\sigma_k} \quad \forall k,j \tag{1.12}$$

$$\mathbf{e}^{new} = \left[(\mathbf{I}-\mathbf{C}^{new})^{-1}\right]'\mathbf{d} \tag{1.13}$$

Proof. See Appendix A.2. ■

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 A.3.

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

1.2.5 Supply: Fuel switching

As described above, producers will react to carbon pricing by reducing the share of CO_2 intensive intermediate goods. This changes the supply chain structure $\mathbf{C}$ and, as a result, total emissions embodied in products k, ε_k. This dynamic 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 $\mathbf{C}$ and thus total emissions intensities ε_k, I allow producers to adjust the mix of fossil fuels used directly in production. This alters direct emission intensities δ_k, 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[9]—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 (1.8).

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 my 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_k^{new}) of the electricity sector and in turn lowers the indirect emission intensities (ε_k^{new}) of all downstream sectors that use electricity at some point in their value chain.

[9] I 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.

1.3 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). Estimates use yearly cross-sections of these data, which are available between 1996 and 2009. 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.

1.3.1 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. In the WIOD data this translates into 1400 varieties ($K = J = 40 \times 35$).

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) as well as price elasticities. For the latter, I follow Fajgelbaum and Khandelwal (2016) in assuming that there is symmetric substitution within each sector s between goods from different countries i, but no substitution between sectors:

$$\gamma_{ii'}^{ss'} = \begin{cases} -\left(1 - \frac{1}{N}\right)\gamma^s & \text{if } i = i' \text{ and } s = s' \\ \frac{1}{N}\gamma^s & \text{if } i \neq i' \text{ and } s = s' \\ 0 & \text{otherwise} \end{cases} \tag{1.14}$$

In short, consumers can substitute textiles from the United States with textiles from India, but they cannot substitute textiles with minerals. I then only need to identify 35 sector-level parameters (γ^s) to find price elasticities. Trade costs between country-pairs (t_{ni}) are of the iceberg variety, implying the typical no-arbitrage condition:

$$\frac{p_{ni}^s}{p_i^s} = t_{ni} \tag{1.15}$$

Specifically, I assume that bilateral trade costs between origin i and destination n are $t_{ni} = d^{\rho}\Pi_l \left(g_{l,ni}^{\delta_l}\right)\eta_{ni}$, where d_{ni} is distance and ρ is the distance elasticity of trade costs. Other bilateral gravity characteristics are in $g_{l,ni}$. Following Fajgelbaum and Khandelwal (2016), we get an estimating equation for the aggregate expenditure of goods from sector s and country i by consumers in country n, $S^s_{ni} = \frac{X^s_{ni}}{Y_n}$:

$$S^s_{ni} = \frac{Y^s_i}{Y_W} + \alpha_i(S^s_n - S^s_W) - (\gamma^s\rho^s)D_{ni} + \sum_j(\gamma^s\delta^s_j)G_{j,ni} + (\beta^s_i - \alpha_i\overline{\beta}^s)\Omega_n + \varepsilon^s_{ni} \quad (1.16)$$

Aggregate expenditure shares (S^s_{ni}) are observed in WIOD (bilateral trade flows in final consumption). Consumers in n buy more goods from sector s in origin country i if that sector is a large relative to the world economy ($\frac{Y^s_i}{Y_W}$) and if consumers in n spend more on goods in sector s relative to the rest of the world ($(S^s_n - S^s_W)$). Variation in trade costs helps identify price elasticities (γ^s). If trade is more concentrated among less distant country pairs within one sector than another, I estimate the former to face a higher price elasticity of demand. 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 ($G_{j,ni}$).

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^s_i). If richer countries, or more unequal countries, consume relatively more textiles from the United States than from India, then I estimate the former to have a income elasticity than the latter. Ω_n is calculated using country-level population and income (GDP) from the Penn World Tables and the Gini index of income inequality from the World Income Inequality Database (WIID). I assume that individual expenditure x_h is proportional to income, i.e. that there is a constant savings rate[10]. Assuming a log normal income distribution, the Gini index is easily converted into the required Theil index[11]. 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 (1.16), I identify the following parameter estimates: $\hat{\alpha}_i$, $\widehat{(\beta^s_i - \alpha_i\overline{\beta}^s)}$, $\widehat{(\gamma^s\rho^s)}$. A second estimation equation helps to identify the missing parameters $\hat{\overline{\beta}}^s$. I estimate an Engel curve projecting aggregate expenditure shares in country n for sectors s on the inequality-adjusted real income y_n:

$$S^s_n = \alpha^s + \overline{\beta}^s y_n + \varepsilon^s_n \quad (1.17)$$

This estimation helps to identify what Fajgelbaum and Khandelwal (2016) call the "sectoral betas", the sector average income semi-elasticities, $\overline{\beta}^s$. ε^s_n is the specific taste of importer n for sector s. These estimates $\hat{\overline{\beta}}^s$ together with the estimates of $\hat{\alpha}_i$ from the

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

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

above gravity estimation are sufficient to identify origin-sector specific income semi-elasticities $\hat{\beta}_i^s$. Finally, to pin down price elasticity parameters $\hat{\gamma}^s$, I follow Novy (2013) (and Fajgelbaum and Khandelwal, 2016) in setting $\rho^s = \rho = 0.177$ for all s.

1.3.2 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:

$$S_{jk} = \frac{\phi_{jk} f_{jk}}{P_k X_k} = a_{jk} \phi_{jk}^{(1-\sigma_k)} P_k^{(\sigma_k - 1)} \tag{1.18}$$

I consider bilateral inter-industry trade flows between 1.96m (1400^2) industry pairs—destination sector k in country n from origin sector s in country i. Again, I assume that each sector s in origin i produces a distinct input variety ($J = S \times I$) and that the market for intermediate goods is perfectly competitive. I further assume that prices are the same for goods from sector s whether they are used as intermediates or final goods ($p_i^s = \phi_i^s$) and that traded goods are subject to iceberg trade costs t_{ni} between destination n and origin i, $p_{ni}^s = t_{ni} p_i^s$. Finally, I assume that production functions are identical for each destination sector k across countries n ($\sigma_{n,k} = \sigma_k$ and $a_{ni}^{ks} = a_i^{ks}$, $\forall n$). Each sector k in destination n will then spend the following share on intermediate inputs from sector s in origin i:

$$S_{ni}^{ks} = a_i^{ks} (t_{ni})^{(1-\sigma_k)} (p_i^s)^{(1-\sigma_k)} (P_n^k)^{(\sigma_k - 1)} \tag{1.19}$$

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

$$\begin{aligned} \log\left(S_{ni}^{ks}\right) &= \log\left(a_i^{ks}\right) + (1-\sigma_k)\log(t_{ni}) + (1-\sigma_k)\log(p_i^s) - (1-\sigma_k)\log\left(P_n^k\right) \\ &= (1-\sigma_k)\log(t_{ni}) + \lambda_n^k + \omega_i^s \end{aligned} \tag{1.20}$$

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 preferences[12]. I use this simple gravity equation to estimate the sector-specific CES production elasticities σ_k. Again, I identify σ_k using cross-sectional variation in bilateral trade costs t_{ni} and assume that $t_{ni} = d_{ni}^{\rho} \Pi_l \left(g_{l,ni}^{\delta_l}\right) \eta_{ni}^{ks}$, where d_{ni} is distance, ρ is the distance elasticity of trade costs, and $g_{l,ni}$ are other gravity variables. The final

[12]Anderson and Van Wincoop (2003) use market clearing conditions and assumptions of symmetry to transform equation (1.19) 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.

estimating equation is:

$$\log\left(S_{ni}^{ks}\right) = (1-\sigma_k)\rho\log\left(d_{ni}\right) + \sum_{l}\left[(1-\sigma_k)\delta_l \log G_{l,ni}\right] + \lambda_n^k + \omega_i^s + \varepsilon_{ni}^{ks} \tag{1.21}$$

Again, I obtain data on the bilateral distance between country pairs (d_{ni}) from CEPII. The other elements of $G_{l,ni}$ are indicators for common language and a shared border, also from CEPII. I estimate this equation separately for the 35 industries k[13].

[13]For estimation, I apply an ordinary least squares (OLS) estimator with origin (country-sector) and destination (country-sector) fixed-effects. This has been shown to be consistent (e.g. Head and Mayer, 2014). I again assume that $\rho = 0.177$.

1.3.3 Model overview and parameter estimates

Table 1.1 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 (β_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) identified from variation in bilateral trade cost. Both income and price elasticities of demand are estimated from equations (1.16) and (1.17) using WIOD data on bilateral trade in final consumption following Fajgelbaum and Khandelwal (2016).

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. Gravity equation (1.21) yields estimates of the 35 CES production elasticities (σ_k) identified from variation in bilateral trade cost. These are estimated from data on inter-industry trade flows and again identified from variation in bilateral trade cost. The Appendix provides an overview of some of these parameter estimates. Estimated parameters are highly consistent across different years[14].

Table 1.1: Method overview

	Theory	**Parameters**	**Data**
Demand	AIDS preferences (non-homothetic)	Income elast. (β_i^s) Price elast. (γ^s)	WIOD: final goods trade (35 sectors, 40 countries)
Supply: Input substitution	CES production (per sector)	CES elast. (σ_k)	WIOD: inter-industry trade (35 sectors, 40 countries)
Supply: Fuel switching	CES production (per sector)	CES elast. (σ_k)	WIOD: fossil-fuel shares (coal, gas, oil)

Notes: This table provides a brief overview of the key model characteristics and data sources.

[14] For example, I consistently estimate agriculture to be a necessity ($\hat{\beta}_s < 0$) and real estate services to be a luxury good ($\hat{\beta}_s > 0$). Within sectors, varieties from the United States and Japan appear more likely to be luxury goods, while varieties from India and Indonesia are necessities.

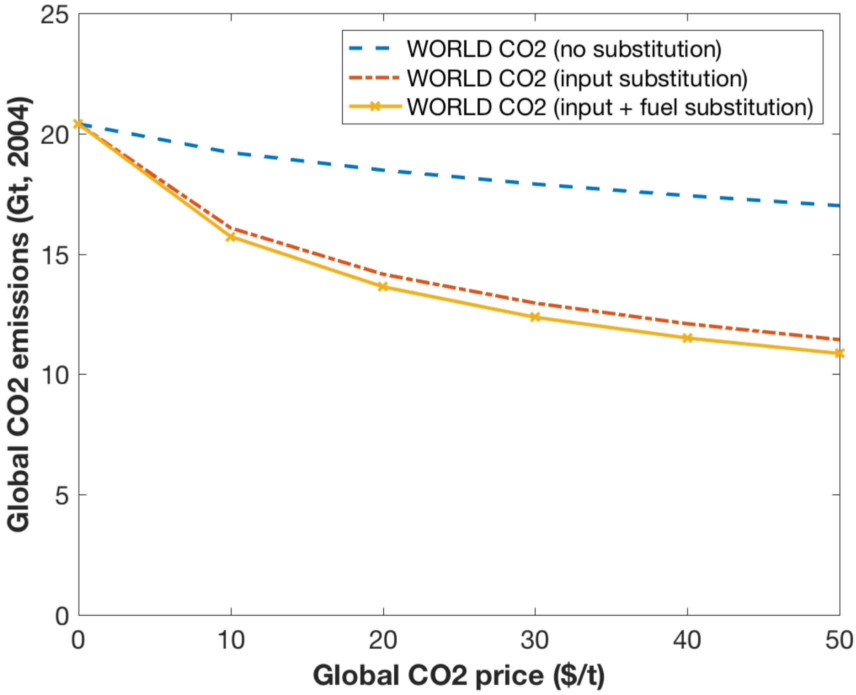
The relative importance of the different adjustment margins of demand and supply can be demonstrated using the results of counterfactual carbon pricing scenarios. Figure 1.1 summarises the predicted potential for global CO_2 emissions reductions under different levels of a global uniform carbon price. 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 CO_2 emissions in the 40 WIOD countries[15]. 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 (blue, dashed line). 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.

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 (red, dash-dotted line). Finally, I estimate that fuel switching adds a further 0.6 Gt in annual emissions reductions (yellow, solid line). For the rest of this chapter, 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). Each of these dynamics may bias the results presented in this chapter as long as any such adjustment systematically falls on either richer or poorer consumers. 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). Arguably, estimating the distribution of the consumer cost as I do here can inform the design of revenue recycling measures.

[15]This 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.

Figure 1.1: Global price - Global CO_2 emissions



Notes: This figure shows global aggregate CO_2 emissions under different levels of a global uniform carbon price in USD per ton of CO_2 simulated in 2004 (WIOD, 40 countries, 35 sectors). 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.

1.4 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. As a first scenario, I simulate a world in which all 40 countries in my sample implement a uniform price on carbon emissions. This is what economic theory may suggest based on efficiency grounds to meet the global climate externality. 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, this 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 an EU-wide carbon price with Border Carbon Adjustments (BCA) that target the emissions content of imported goods.

1.4.1 Scenario 1: A global uniform carbon price

I estimate the consumer cost from introducing a global uniform carbon price of 30 USD/t[16]. Figure 1.2 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. More negative values represent a higher cost. The solid line shows a 10th degree polynomial approximation thereof. The blue band represents 95% confidence intervals[17]. 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—equivalent to them loosing 1.8% to 2.2% of their annual income—is more than twice as large as that of consumers in the top 10 %.

A second insight is that the distributional incidence can differ between countries. To see this, Figure 1.3 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 income distributions. Upward-sloping lines suggest that in those countries carbon pricing is regressive—with larger relative costs to lower income consumers—and vice versa. The distributional incidence of carbon pricing in

[16]Some 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 A.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.

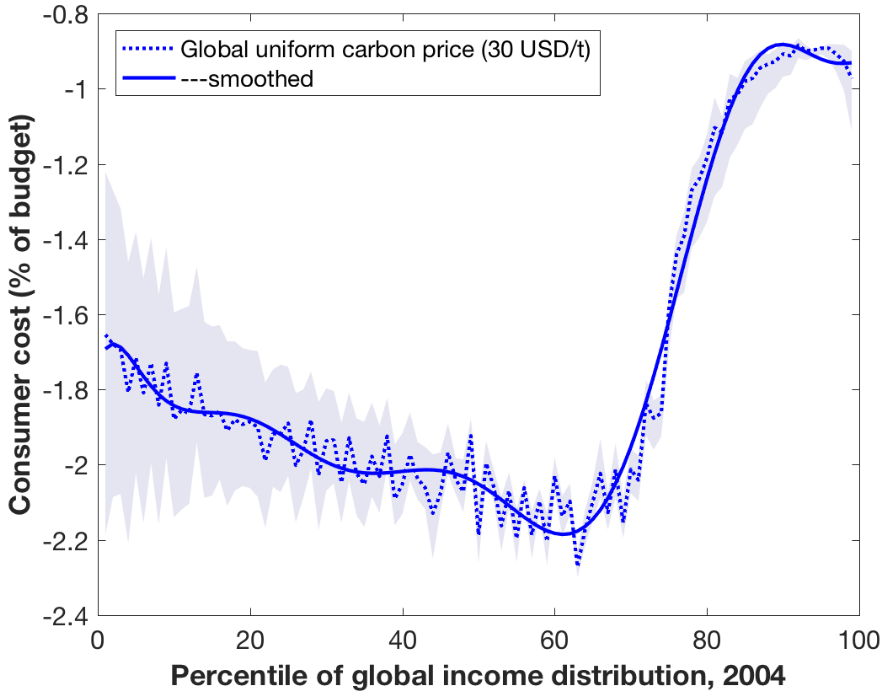
[17]Confidence intervals are from 500 separate simulations, each using a different set of model parameters drawn from the joint normal distributions for parameter estimates from estimations (1.16), (1.17) and (1.21).

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; Dorband et al., 2019). However, Figure 1.3 also suggests a third, more nuanced insight. The slope of individual lines in Figure 1.3 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 1.4 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.

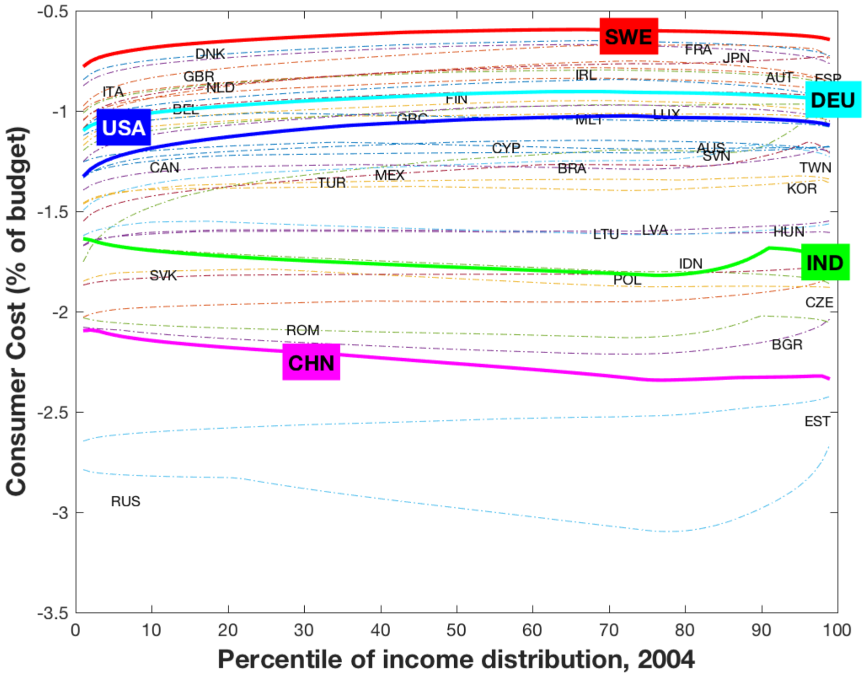
Finally, Figure 1.5 translates the relative consumer cost from Figure 1.2 into absolute dollar values. While carbon pricing results in a larger relative cost for poor consumers, the absolute cost is still largest for consumers with the highest incomes. Put differently, the unequal distribution of consumption expenditures across the global results in rich consumers paying the bulk of the absolute cost of pricing carbon.

Figure 1.2: Global price of 30 USD/t - Global distribution of consumer cost



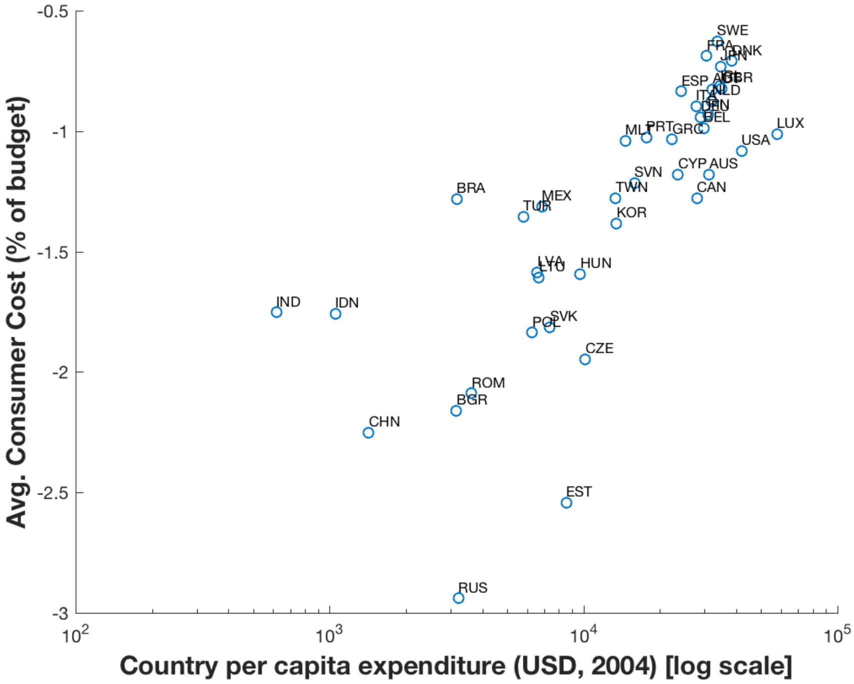
Notes: This figure shows the global distribution of the consumer cost under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution across the 4.2 billion inhabitants of the 40 WIOD countries 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 (1.16), (1.17) and (1.21).

Figure 1.3: Global price of 30 USD/t - Within-country consumer cost



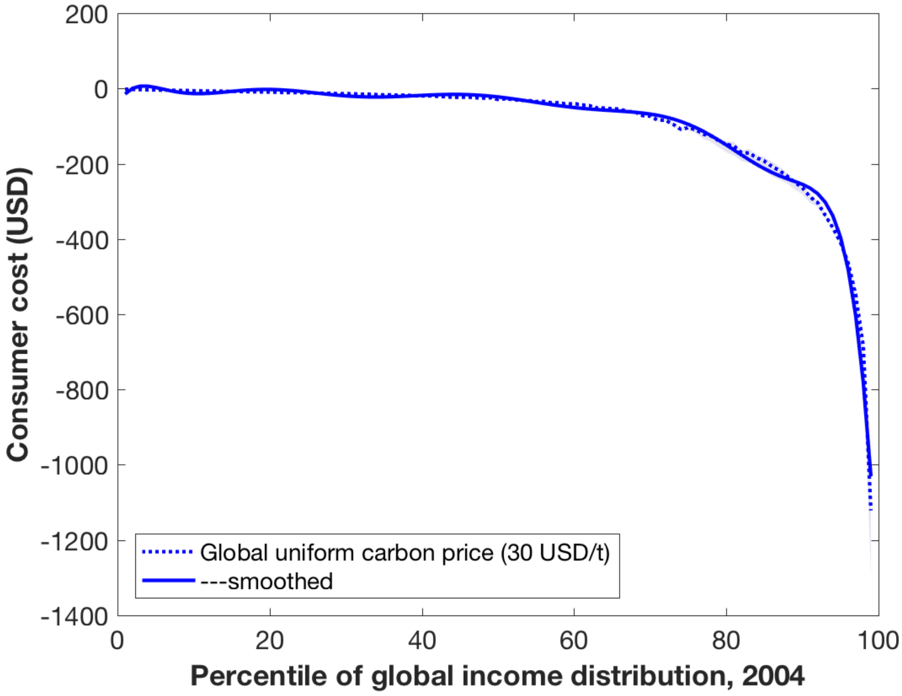
Notes: This figure shows the distribution of the consumer cost in each country under a global uniform carbon price of 30 USD per ton of CO_2 simulated in 2004 (40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution within each of the 40 WIOD countries in 2004.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

Figure 1.4: Global price of 30 USD/t - Between-country consumer cost



Notes: 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 1.5: Global price of 30 USD/t - Global distribution of consumer cost (USD)



Notes: 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 (1.16), (1.17) and (1.21).

1.4.2 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)[18]. 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[19]. I simulate a carbon price of 30 USD/t in the 27 EU member countries levied on all emissions in the sectors targeted by the ETS at launch[20].

Figure 1.6 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 0.8% of their total expenditure. The cost to consumers in the top half of the income distribution is less than 0.3%. Again, the distribution of consumer cost is largely driven by differences between countries rather than within. Figure 1.7 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. Consumers in Romania experience a much higher cost than consumers in Germany or Sweden, no matter if they have high or low incomes.

Figure 1.8 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—and in particular power

[18]Among 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.

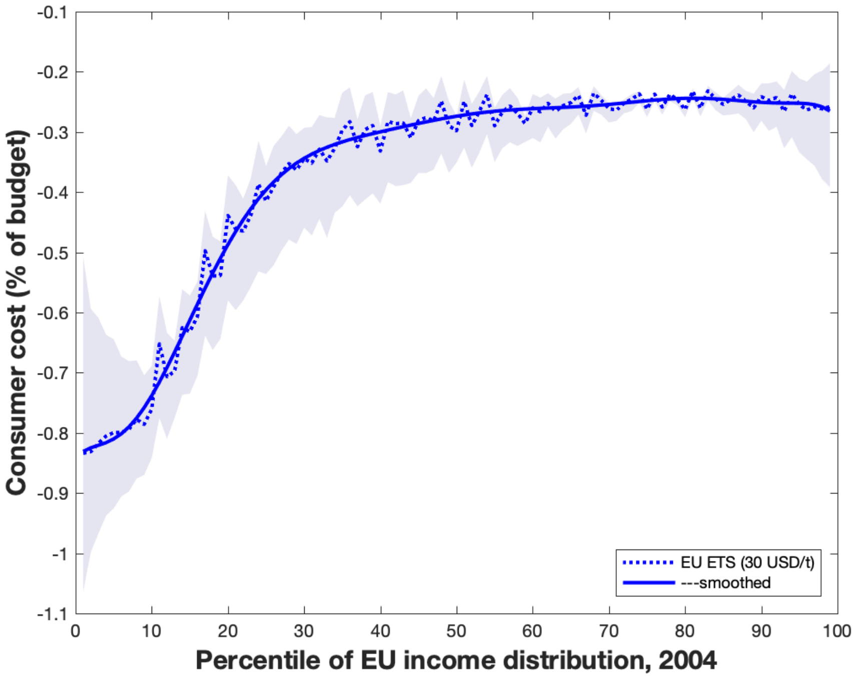
[19]The first phase of the EU ETS, running from 2005 to 2007, was considered a learning phase. Almost all allowances were initially distributed free of charge based on estimates. Due to oversupply, the allowance price collapsed in 2007.

[20]The EU ETS covered about half of total CO_2 emissions, mostly in power generation and energy-intensive industries. To emulate the intended sector targeting of the first phase of the EU ETS, I apply the carbon price to emissions in the following WIOD sectors: "Electricity, Gas and Water Supply", "Mining and Quarrying", "Pulp, Paper, Printing and Processing", "Coke, Refined Petroleum and Nuclear Fuel", "Chemicals and Chemical Products", "Other Non-Metallic Mineral", and "Basic Metals and Fabricated Metal". While these sectors may not be fully congruent with the actual targeting of the EU ETS, which e.g. discriminated by plant size within industry, it should come close. Notably, the distribution of costs presented here is qualitatively similar, albeit smaller, than the costs under a scenario where the EU carbon price applies to all sectors.

generation—in lower-income countries. Estonia is a case in point, where the high penetration of shale oil results in particularly large consumer costs from carbon pricing. As expected, the policy has close to no cost to consumers in countries outside of the 27 EU states. 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 1.9. The median EU consumer incurs a welfare loss of ca. 60-70 USD from an EU-wide carbon price of 30 USD/t in 2004.

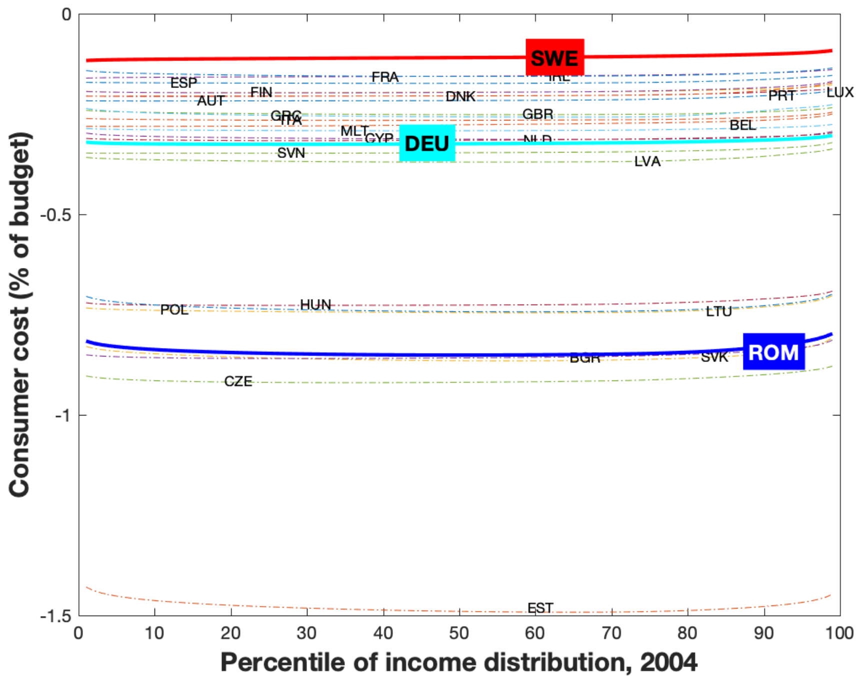
It is important to note that my analysis is an *ex ante* evaluation of the EU ETS as it may have been intended. I do not evaluate the EU ETS as it was realised. There are a number of reasons why the realised outcome of the EU ETS may have differed from my simulation. The EU ETS, and in particular the first phase, has been fraught by a range of implementation and design issues. A large literature documents these and evaluates the effects that the EU ETS had (surveyed for example in Ellerman et al., 2016; Martin et al., 2016). But my results suggest one characteristic of the EU ETS which has received less attention—the potential regressive effects of carbon pricing across EU citizens, which could disproportionately affect consumers in Eastern European and Baltic member states.

Figure 1.6: EU price of 30 USD/t - EU distribution of consumer cost



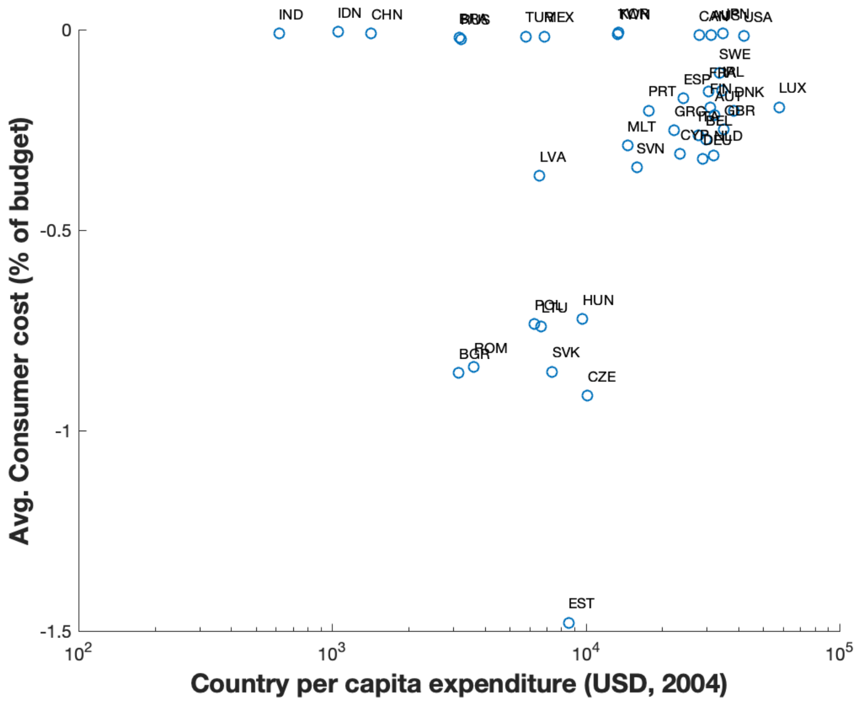
Notes: This figure shows the global distribution of the consumer cost under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to the EU ETS target sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution 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 (1.16), (1.17) and (1.21).

Figure 1.7: EU price of 30 USD/t - Within-country consumer cost



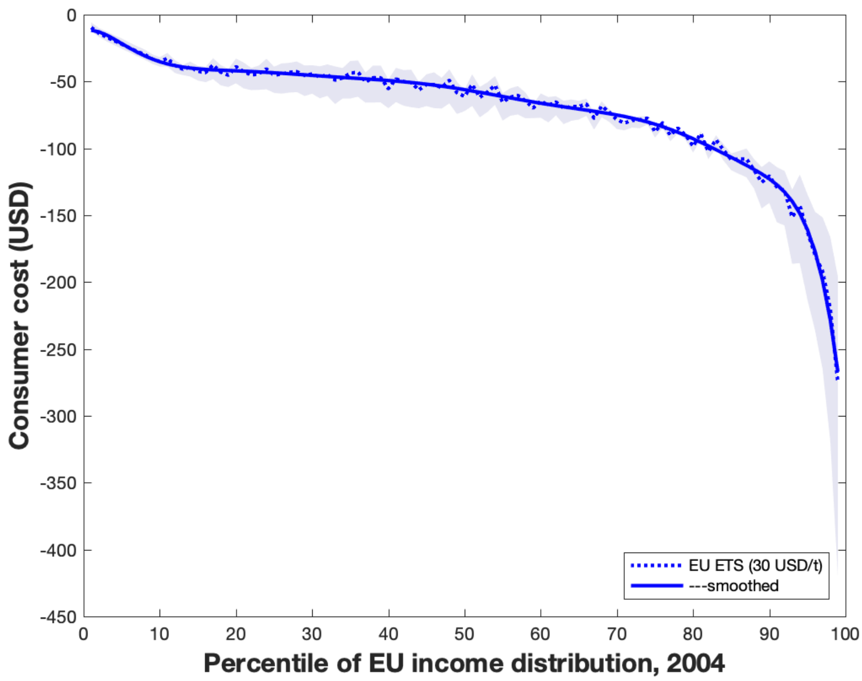
Notes: This figure shows the distribution of the consumer cost in each country under an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to the EU ETS target sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution 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 1.8: EU price of 30 USD/t - Between-country consumer cost



Notes: 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, applied to the EU ETS target sectors and 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 1.9: EU price of 30 USD/t - EU distribution of consumer cost (USD)



Notes: 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, applied to the EU ETS target sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles of the income/expenditure distribution 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 (1.16), (1.17) and (1.21).

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

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). Governments can be concerned both about the actual damage to industrial competitiveness as well as potential resistance to carbon pricing from a perceived threat.

Border Carbon Adjustments (BCA) could help reduce the potential damage from weakened competitiveness. Their basic function is to extend the coverage of a carbon price, targeting goods from countries with less stringent carbon pricing regimes (Felder and Rutherford, 1993). BCA are most commonly proposed in the form of carbon tariffs on the embodied carbon of imported goods. 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 distributional 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 third scenario, in which a carbon price of 30 USD/t in the EU is extended to traded goods[21].

Figure 1.10 shows how the additional cost of complementing an EU-wide carbon price of 30 USD/t with a BCA is distributed. Across the 490 million residents of the EU, I estimate that welfare losses follow an inverse U-shape. 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 1.11 shows the distribution of the consumer cost within countries. 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. This pattern might be due to both groups consuming larger shares of imported goods which experience a price increase due to BCA. At the bottom of the income distribution this is driven by imported necessities (e.g. textiles from India), while at the top it is driven by imports with relatively higher income elasticities (e.g. textiles from the United States).

Contrary to the other two scenarios, the cost of BCA varies more strongly within

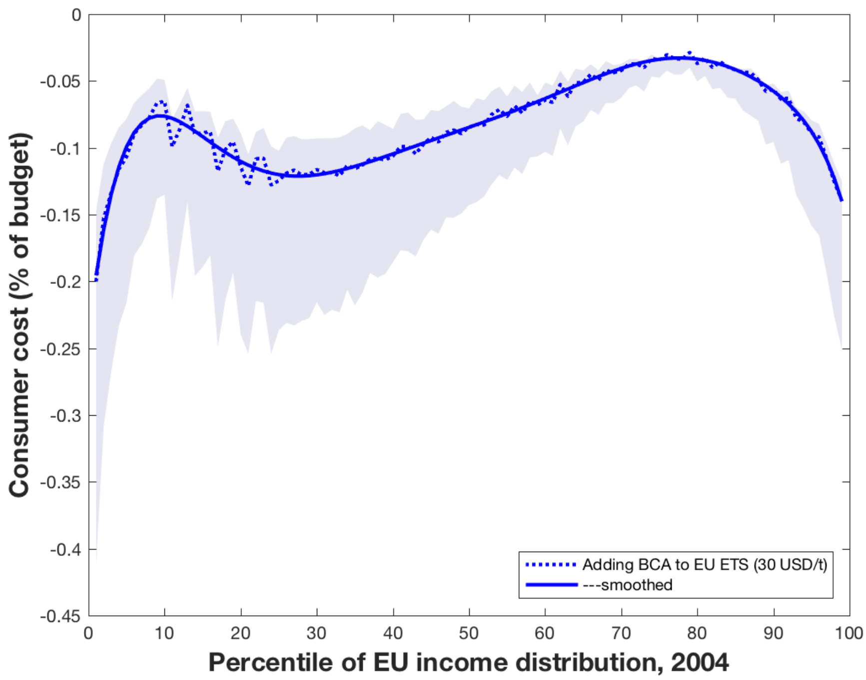
[21]In the analysis of the EU ETS, I limited carbon pricing to emissions in energy-intensive sectors that were initially targeted by the EU ETS. Here I consider BCA to complement a domestic carbon price covering all sectors. The results are qualitatively similar—albeit with smaller costs—for a BCA to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

countries than between them. Figure 1.12 shows the average consumer cost for the 27 EU member countries. Differences between countries are rather small—with perhaps Cyprus as the notable exception—and there is no clear relationship with national income levels. This may be due to a relatively similar composition of aggregate imports into the different EU countries. Figure 1.13 again shows the distribution of consumer costs in absolute terms. Complementing an EU-wide carbon price with a BCA would have result in a cost to the median EU consumer of about 20 USD in 2004.

Leakage reduction: This chapter 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 applied to all sectors 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[22]. 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 considering the additional gains in tariff revenue, domestic production gains, and climate mitigation benefits to the rest of the world.

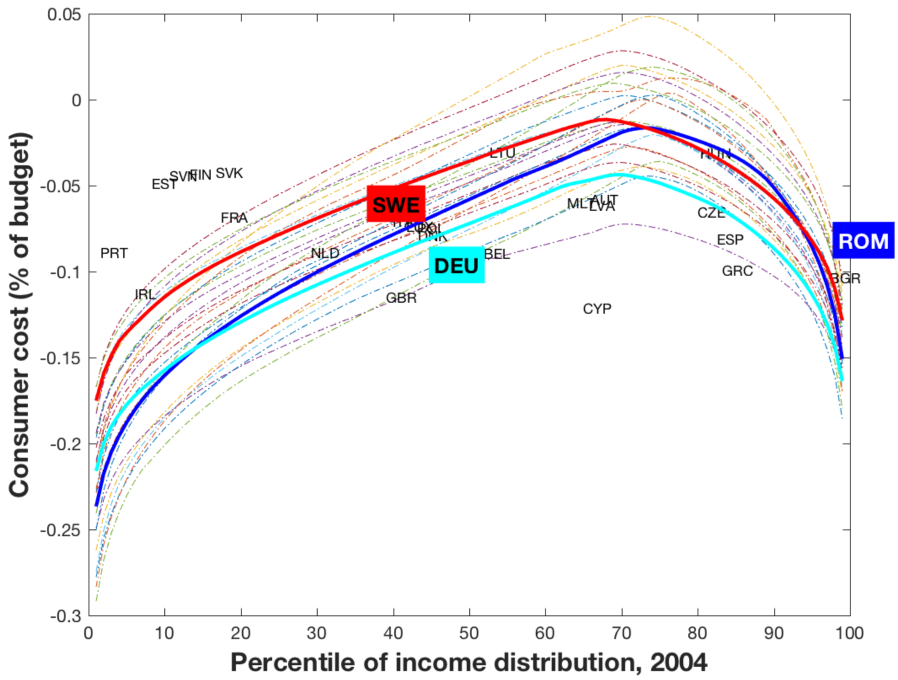
[22]Studies using rich Computational General Equilibrium models (e.g. Elliott et al., 2010; Böhringer et al., 2016a,b) find that BCA have the potential to significantly reduce carbon leakage and shift the economic burden of emission reduction to countries without domestic carbon prices (Aldy and Pizer, 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.

Figure 1.10: EU Border Adjustment of 30 USD/t - EU distribution of consumer cost



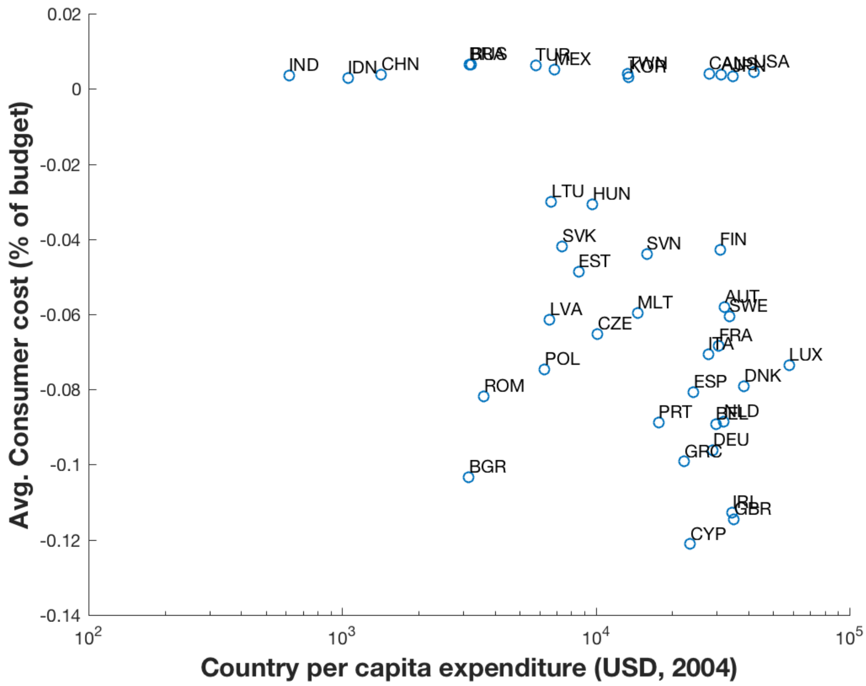
Notes: This figure shows the global distribution of the consumer cost under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied to all sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows percentiles 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 (1.16), (1.17) and (1.21).

Figure 1.11: EU Border Adjustment of 30 USD/t - Within-country consumer cost



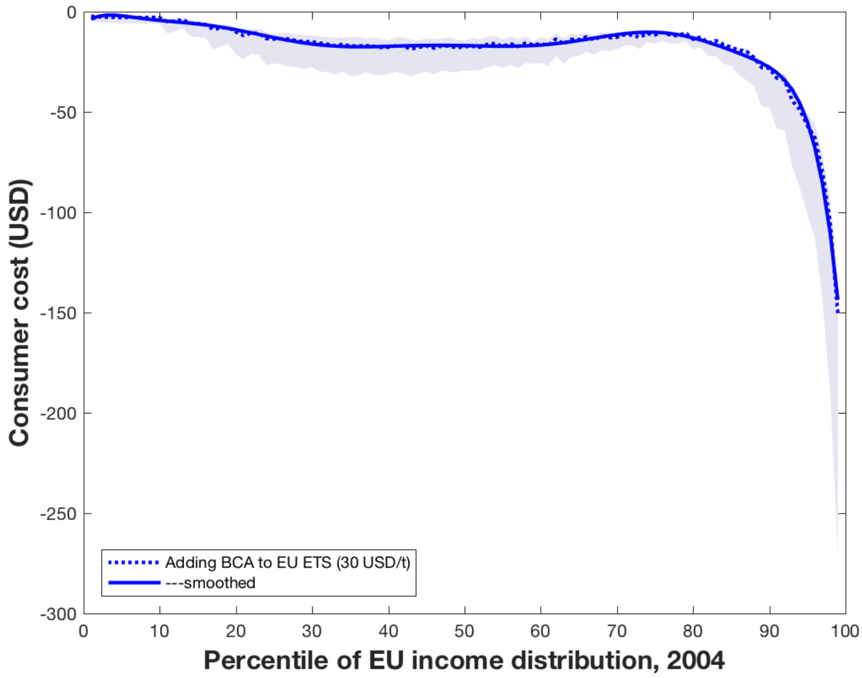
Notes: This figure shows the distribution of the consumer cost in each country under a Border Carbon Adjustment to complement an EU-wide (27 countries) uniform carbon price of 30 USD per ton of CO_2, applied all sectors and simulated in 2004 (model includes 40 WIOD countries). The horizontal axis shows 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 1.12: EU Border Adjustment of 30 USD/t - Between-country consumer cost



Notes: 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, applied to all sectors and 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 1.13: EU BCA of 30 USD/t - EU distribution of consumer cost (USD)



Notes: 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, applied to all sectors and 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 (1.16), (1.17) and (1.21).

1.5 Robustness

The results reported in Section 1.4 rely on a number of model assumptions stated in Section 1.2 as well as the parameter estimates obtained in Section 1.3. In this section, I report results from robustness checks which support my confidence in the provided estimates.

1.5.1 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 countries[23]. 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 and fewer textiles from India. This is of course a rather strong assumption.

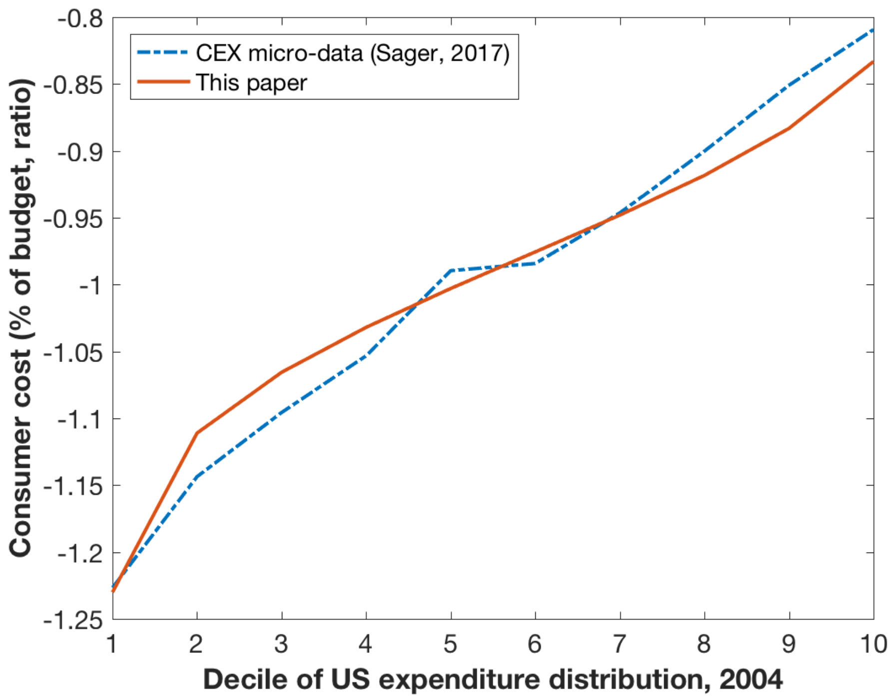
To test this assumption, I compare the within-country expenditure distribution derived from my model to micro-data from the United States. I focus on the initial incidence of carbon pricing in the United States, which can be thought of as the cost to consumers of introducing a carbon price of 1 USD/t before any demand substitution takes place. Figure 1.14 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). Both are normalised to 1 on average. The CEX reports consumer expenditures on over 600 categories, which I map into the 35 WIOD sectors[24]. 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.

[23]The 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 step in this 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.

[24]Data and methods used to derive the CEX welfare exposure are described in detail in Chapter 2. Both are normalised by dividing through the marginal welfare effect of the average consumer.

Figure 1.14: Comparison of model fit to micro-data - Marginal incidence



Notes: This figure compares the fit of the demand system (this chapter) 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 Chapter 2). 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.

1.5.2 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, Figure 1.2 shows the distributional incidence for about 4.2 of the world population of around 7 billion people.

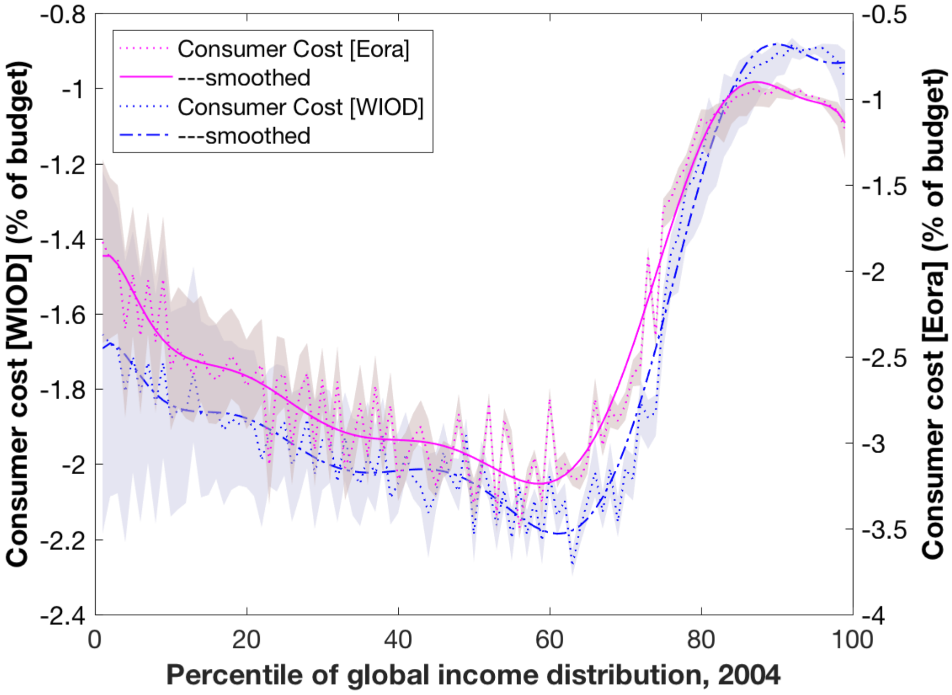
To check for the robustness of my results, I re-estimate the above incidence based on an alternative MRIO data source—the Eora MRIO database. Eora provides more comprehensive coverage. I use the symmetric and harmonised version of Eora (Eora 26), which covers 189 countries and 26 sectors. The most recent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

Figure 1.15 compares model estimates using Eora data to those obtained using WIOD. The left panel is equivalent to Figure 1.2—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 (and model parameters) 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 gases[25] 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 Appendix A.6.

[25] Specifically, the data includes six Kyoto gases and gas groups as reported in the PRIMAP-hist database: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), hydrofluorocarbons(HFCs), and perfluorocarbons (PFCs). Results look qualitatively similar if the analysis is restricted to CO_2 emissions from fossil-fuel combustion as reported by the IEA.

Figure 1.15: Comparison to global incidence estimates using Eora data



Notes: This figure compares simulation results using WIOD data (used throughout this chapter) 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 1.2. 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 (1.16), (1.17) and (1.21).

1.5.3 Alternative modelling approaches

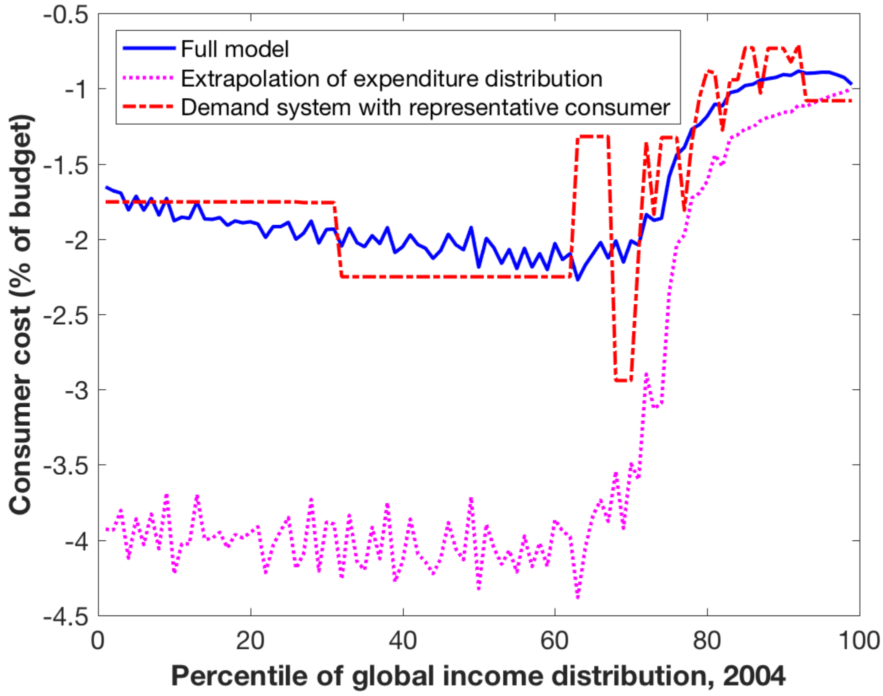
Much of the literature estimates the within-country incidence of energy taxes using data from consumer expenditure surveys (Grainger and Kolstad, 2010; Williams et al., 2015, e.g.). These provide detailed micro-data on observed consumer behaviour. We have seen above that my global model matches well 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 1.16 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 regressivity[26].

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 (1.6) 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 cost[27].

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

[27]Using Equation (1.6), the variation in cost to consumers h in countries n can be disaggregated as: $\mathtt{Var}\left(\hat{\omega}_{n,h}\right) = \mathtt{Var}\left(\hat{W}_n\right) + \mathtt{Var}\left(\hat{\psi}_h\right)$.

Figure 1.16: Comparison of global incidence estimates by modelling choice



Notes: 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 1.2. 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 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.

1.6 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 the other costs and benefits of climate policy (Fullerton, 2011). In particular, it should be compared to two important benefits of carbon pricing—the benefits of climate mitigation and the benefits of using the collected revenue.

First, the net costs of carbon pricing should be contrasted with the benefits of reduced climate damage (see Dietz et al., 2018, for a recent survey). The benefit of reducing CO_2 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 (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, 2019). 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.

In this chapter, I do not attempt to systematically compare the consumer cost of carbon pricing to the benefits of climate mitigation. For illustrative purposes, Figures 1.17 and 1.18 show the country-level cost to consumers under a global price of 30 USD per ton of CO_2 in 2015. For this illustrative map, I again use Euro data which contains information on 189 countries[28]. 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 1.17 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

[28]Eora achieves greater coverage in part due to extrapolation when primary data sources are missing. It has generally been shown to match other MRIO data sources quite well (Moran and Wood, 2014). But it may be less reliable for certain small and less developed economies with poor availability of primary data. I use the more reliable WIOD in my main analysis of Section 1.4.

most from climate mitigation. Figure 1.18 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).

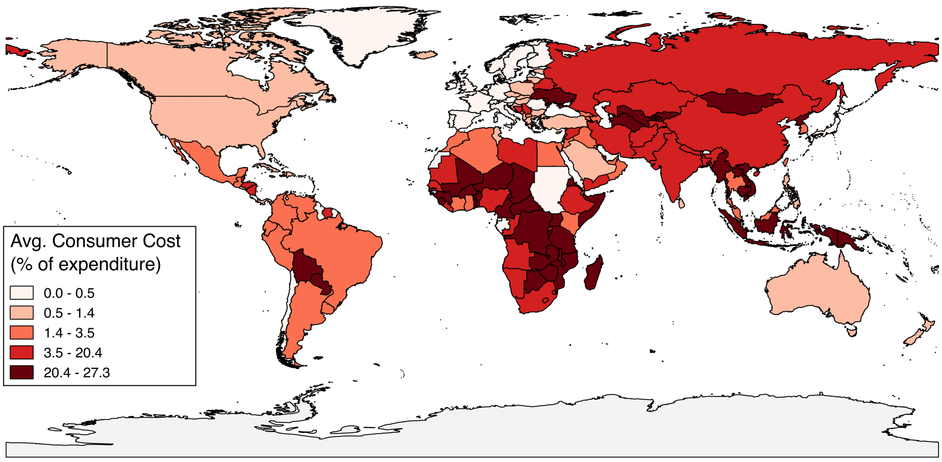
Overall, I find a regressive consumer cost of carbon pricing schemes—both in the form of a uniform global carbon price and the EU ETS. Meanwhile, the incidence of climate mitigation benefits is likely progressive across countries—with particular benefits to countries that are both hot and poor. These 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.

Second, the incidence of any carbon pricing scheme will ultimately depend on the use of revenues. There may be significant benefits from redistributing revenue collected by a carbon pricing scheme. While the collected revenue from a carbon tax (or a permit auction) may not 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. 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; Williams et al., 2015) or other progressive measures such as food subsidies Gonzalez (2012). In short, how the revenue of carbon pricing is redistributed can entirely alter its distributional effect.

This is also what I find in my global incidence analysis. Illustrating this point, the average global consumer cost of 1.7% in Figure 1.17 falls to 0.2% (162 billion USD) when revenues are subtracted. How the difference of 1.5% is distributed may then alleviate or even overturn any regressivity of the 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).

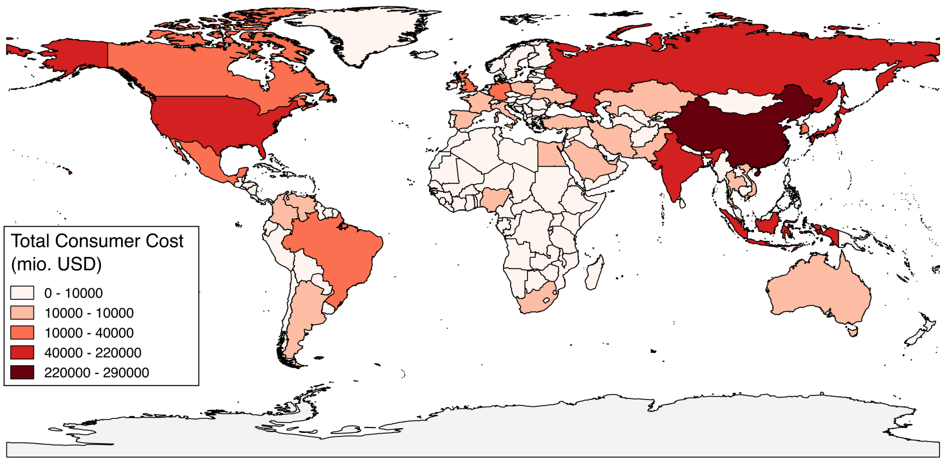
In conclusion, this chapter is the first to estimate how the consumer cost of carbon pricing is distributed globally—both between and within many countries. As any large-scale welfare analysis, my results rely on a number of assumptions and empirical estimates. I have shown that my findings replicate 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 1.17: Global price of 30 USD/t in 2015 - Country average consumer cost



Notes: 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 1.18: Global price of 30 USD/t in 2015 - Country total consumer cost



Notes: 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.

Chapter 2

Inequality and Carbon Consumption: Evidence from Environmental Engel Curves

In this chapter, I investigate the relationship between income inequality and the carbon dioxide (CO_2) content of household consumption. I quantify household carbon by linking household expenditure to carbon content using input-output analysis. I then estimate Environmental Engel curves (EECs) that describe the relationship between household income and CO_2 in the United States between 1996 and 2009. A second-degree polynomial specification in income approximates well the fit of more flexible nonparametric models. Using these parametric EECs, I decompose the change in emissions over time—due to both shifts of EECs and movements along them—as well as the distribution of CO_2 across households. In both cases, income is an important driver of emissions. Finally, I describe a potential "equity-pollution dilemma"—progressive income redistribution may raise aggregate emissions. I estimate that progressive income transfers may raise household carbon by 5.1% at the margin and by about 2.3% under complete redistribution.

2.1 Introduction

Income inequality and its consequences are today the focus of much research (for an overview see e.g. Atkinson et al., 2011). At the same time, curbing greenhouse gas emissions responsible for global warming is recognised as a major policy issue. In Chapter 1, I asked how the cost of one policy to curb emissions, carbon pricing, is distributed across consumers around the world. In this chapter, I investigate the interplay between the distribution of income within a country and the greenhouse gas emissions content of household consumption. A large body of research investigates how the burden of pollution is distributed across rich and poor households. Evidence points to regressive effects of both local environmental externalities, such as air pollution (Hsiang et al., 2019), and global ones, such as climate change (Hsiang et al., 2017). This chapter is interested in the inverse of that relationship, asking if and how the distribution of income may affect aggregate environmental outcomes and in particular greenhouse gas emissions.

In a first step, I calculate the carbon dioxide (CO_2) emissions linked to the consumption of households in the United States, covering the period between 1996 and 2009. To do so, I link households' annual expenditures on different items (in \$) to the carbon intensity of these items (CO_2/\$). I capture total emissions—including direct emissions from energy and fuels (e.g. heating, electricity, transportation fuels) as well as indirect emissions embedded in the value chain of goods and services. I calculate the latter using input-output based emissions accounting.

I then estimate Environmental Engel curves (EECs), which represent household carbon at different levels of income. Just like EECs for air pollutants (Levinson and O'Brien, 2019), I find EECs for CO_2 to be upward-sloping and concave. This implies that embedded CO_2 is a normal good (income elasticity above 0) that behaves like a necessity (elasticity below 1). I also find that EECs are shifting downwards over time—each level of income is linked to less CO_2 in later years.

I use EECs to investigate the contribution of different factors to the evolution of carbon emissions over time and their distribution across households. Between 1996 and 2009, reductions in emissions intensities lead to a downward shift of EECs despite upward-pressure from income growth and changes in the composition of consumption. While technology is the biggest factor over time, income explains a large part of the variation in household carbon, both over time and across households. Other observed household characteristics—family size, age structure, education, race, and region—play only a minor role. This regression-based decomposition based on quadratic EEC estimates adds to the literature on consumption-based household carbon footprints and their drivers. It complements previous approaches, which often rely on descriptive analyses and single estimates of income elasticities (e.g. Weber and Matthews, 2008;

Buechs and Schnepf, 2013). I demonstrate that a quadratic EEC approximates well the relationship between income and household carbon.

Given the key role of income in shaping household carbon, I then consider the consequences of income redistribution for consumption patterns and emissions. Based on the observation of concave EECs, I formulate and quantify what I call the ”equity-pollution dilemma”—positive income redistribution may raise aggregate household carbon. This contributes to the literature spurred on by the initial formulation of the dilemma by Scruggs (1998) and empirical studies using cross-country analyses following Heerink et al. (2001). As a key contribution, I quantify the dilemma using micro-data on household consumption within a single country.

Based on the quadratic EECs, I quantify the “equity-pollution dilemma” as a function of Gini’s mean difference dispersion measure. For the United States in 2009, I predict that income transfers would have raised household carbon by 5.1% at the margin and by about 2.3% under complete income redistribution. Under a hypothetical scenario with U.S. household income distributed similar to that in Sweden, aggregate emissions would be 1.5% higher. The “equity-pollution dilemma” is larger for CO_2 than for methane (CH_4) and nitrous oxide (N_2O). The proposed method may prove useful for future work on inequality and pollution across countries, time periods and pollutants.

The rest of this chapter is structured as follows. Section 2.2 reviews the previous literature. Section 2.3 discusses the methodology and data used. Section 2.4 presents evidence from descriptive EECs, while Section 2.5 presents results from regression-based, parametric EECs. Section 2.6 quantifies the “equity-pollution dilemma”. Section 2.7 concludes.

2.2 Previous literature

This chapter contributes to two related literatures. The first literature links levels of income inequality within countries to aggregate pollution levels. The second literature is focused on the drivers of carbon footprints across households, with particular attention given to income.

2.2.1 The relationship between inequality and aggregate pollution

The literature highlights two channels through which the income distribution may shape environmental outcomes—consumer choice and political economy[1]. This chapter focuses on the consumption channel of the inequality-pollution relationship as proposed by Scruggs (1998) and formalised by Heerink et al. (2001). Following the simple conceptual framework in Heerink et al. (2001), let us assume that the pollution attributable to household i (y_i) is a function of i's income (m_i) and a household-specific constant (ε_i):

$$y_i = f(m_i) + \varepsilon_i \tag{2.1}$$

As shown by Heerink et al. (2001), if this relationship is non-linear, then we may observe systematic co-movement between income inequality and aggregate emissions. However, the existing empirical evidence does not consistently find such co-movement at the aggregate level (see survey by Berthie and Elie, 2015). Baek and Gweisah (2013) find a positive association between income inequality (measured as Gini index) and per capita CO_2 emissions in the United States between 1967-2008. Meanwhile, Heerink et al. (2001) find a negative association between the Gini index and per capita CO_2 emissions across 180 countries in the period 1961-2001. For local air pollution, Torras and Boyce (1998) find a positive association between the Gini index and pollution across cities and countries between 1977-1991.

Results from these studies are mixed and vary with choice of pollutant, scale of analysis, timing and empirical specification. They also suffer from limitations to drawing inference about the relationship between income inequality and aggregate pollution. Arguably, both levels of inequality and pollution covary with a variety of structural, cultural, economic, and political factors of a country. Simply put, aggregate-level associations may not be causal. This chapter contributes to the literature by using micro-data from a single country to investigate one driver of the inequality-pollution relationship—household consumption.

[1]The political economy channel posits that environmental policy is shaped by differences between rich and poor citizens in levels of political influence and in tastes for environmental quality (Boyce, 1994).

2.2.2 The relationship between household consumption and pollution

Research into the greenhouse gas (GHG) emissions attributable to individual countries, regions, sectors, firms and households is abundant. At the macro-scale, there is a large literature on "Environmental Kuznets Curves" which describe the relationship between economic development and levels of aggregate pollution[2] (following Grossman and Krueger, 1995). At the micro-scale, a growing literature is concerned with the carbon content of individual products (e.g. Tukker and Jansen, 2006) and the consumption basket of households (e.g. Weber and Matthews, 2008). I follow the latter literature by linking the income and socio-economic characteristics of households to the carbon content of their consumption.

Consumption-based GHG accounting has become pervasive (Davis and Caldeira, 2010)[3]. A common finding is that consumption-based GHG emissions are increasing with income. Similar to this chapter, Weber and Matthews (2008) estimate household carbon based on expenditure data from the Consumer Expenditure Survey in the United States. They find that income and household expenditure are the strongest predictors of household carbon. This is mirrored in studies of household fuel use (Papathanasopoulou and Jackson, 2009) and the energy content of household consumption (Lenzen et al., 2006). Further factors that have been found to predict household carbon are household size, age, employment status, educational attainment, urban vs. rural location, and the quality of housing stock (for a recent survey of the literature see Druckman and Jackson, 2015)[4]

While pollution is increasing with income, this relationship may not be linear. Early contributions hypothesised an inverted U-shaped relationship between household income and the pollution intensity of consumption (Kahn, 1998; Heerink et al., 2001). Empirical evidence suggests that the pollution burden per unit of expenditure is indeed decreasing in income (e.g. Liu et al., 2013; Buechs and Schnepf, 2013). This is usually summarised by an income elasticity of CO_2 below 1, with many estimates ranging between 0.8-1.0 (Chakravarty et al., 2009).

Keeping with our simple framework, let us assume there is only one polluting

[2]Some contributions find an inverted-U shape of those "Environmental Kuznets Curves", with low- and high-income countries polluting less than middle-income countries. However, this literature suffers from serious limitations and is largely limited to conditional correlations at the aggregate level (see e.g. Harbaugh et al., 2002). I focus instead on a structural relationship between individual household income and pollution.

[3]Key motivations for consumption-based emissions accounting are the quantification of so-called "carbon leakage" between countries (see surveys by Wiedmann, 2009; Sato, 2014) and the "rebound effect" at the household level (e.g. Thomas and Azevedo, 2013).

[4]A related literature estimates consumption-based household carbon footprints and their association with income globally, highlighting the disproportionate footprints of the rich independent of nationality (Chakravarty et al., 2009; Chancel and Piketty, 2015).

good and the share of income that i spends on that good ($\alpha(m_i)$) is itself a function of income. Normalising pollution units and dropping the constant, equation (2.1) then becomes:

$$y_i = \alpha(m_i) \cdot m_i \tag{2.2}$$

An income elasticity below 1 implies that the expenditure share of the polluting good is decreasing with income ($\alpha'(m) < 0$)[5]. Higher income is associated with a lower emissions-intensity (CO_2/\$) of consumption—pollution behaves like a necessity.

In this chapter, I go beyond a single estimate of income elasticity and estimate Environmental Engel curves (EECs) to describe the carbon content of household consumption as a function of income. I estimate EECs for greenhouse gas emissions embedded in the consumption of households in the United States between 1996 and 2009. In doing so, I follow Levinson and O'Brien (2019), who construct EECs for local air pollutants in the United States. They focus on PM_{10}, but find similar results for VOC, NO_x, SO_2 and CO. Just like EECs for air pollutants, I find carbon EECs to be upward sloping and concave (which jointly implies that $\alpha(m) + \alpha'(m)m > 0$ and $\alpha'(m) < 0$).

Concavity of EECs implies income elasticities below 1 ($\alpha'(m) < 0$). Household carbon is a normal good that acts like a necessity. But EECs allow for more structure, such as income elasticities that vary with income. Fouquet (2014) finds that long-run income elasticities for energy services (domestic heating, lighting, passenger transport) are rising up to a point and subsequently tend towards zero. I find similar trends in my sample (Figures B.4 and B.5 in the Appendix). While electricity is a necessity, gasoline acts like a luxury good at incomes below \$50K and only exhibits shrinking budget shares at incomes above \$100K.

In this chapter, I demonstrate that simple parametric EECs with a quadratic income term match well more flexible nonparametric estimates. One advantage of the parametric specification is that it makes possible the decomposition of household carbon inequality as well as the evolution of average household carbon over time. I then use estimates of EECs to quantify the link between inequality and aggregate pollution proposed by Heerink et al. (2001).

[5]The income elasticity is given by $\eta = \frac{dy(m)}{dm}\frac{m}{y(m)} = 1 + \frac{\alpha'(m)}{\alpha(m)}m$.

2.2.3 The "equity-pollution dilemma"

As shown above, income elasticities below 1 and concave EECs usually go hand in hand. Income elasticities below 1 mean that budget shares of polluting goods tend to decrease with income—emissions behave like a necessity. Expenditure by lower income households has a higher emissions intensity (CO_2/\$). This is often taken to suggest that carbon pricing will be regressive—lower income households will be harder hit from pricing emissions (e.g. Pearce, 1991; Grainger and Kolstad, 2010). In Chapter 1, I found such regressivity to also hold at the global scale. In sum, environmental policy may have undesired distributional effects. However, concave EECs also suggest that redistribution may inadvertently raise aggregate pollution. I call this the "equity-pollution dilemma":

Given that lower income households have a higher propensity for consumption-based emissions from additional income (i.e. EECs are concave), progressive redistribution may raise aggregate emissions.

Simply put, the increase in emissions from the additional consumption of the lower income household will be larger than the reduction from the drop in consumption of the higher income household. While previous contributions tested for this association at the aggregate level (following Heerink et al., 2001), I use consumption micro-data and propose a precise formula to quantify the "equity-pollution dilemma" based on quadratic EECs.

2.3 Data and methodology

I estimate the carbon dioxide (CO_2) emissions in the consumption of households in the United States. Consider that the total emissions of household i are calculated by multiplying her expenditure (in \$) on good k ($c_{i,k}$) with the carbon intensity (CO_2/\$) of consuming k (e_k):

$$y_i = \sum_{k=1}^{K} c_{i,k} \cdot e_k \tag{2.3}$$

This approach is common in the literature on consumption-based emissions (Wiedmann, 2009). While data on expenditures ($c_{i,k}$) is readily available, I calculate the emissions intensities of different consumption categories (e_k). I focus on total emissions—including direct emissions from energy and fuels (e.g. heating, electricity, transportation) as well as indirect or "embedded" emissions in the value chain of goods and services. Once I obtain estimates of household carbon (y_i), I follow Levinson and O'Brien (2019) in estimating Environmental Engel curves (EECs). These describe the relationship between household income and the total CO_2 content of household consumption.

2.3.1 Data

Information on household income, consumption and socio-demographic characteristics come from the United States Consumer Expenditure Survey (CEX). The Bureau of Labor Statistics provides anonymised public use micro-data from 1996 on (Bureau of Labor Statistics, 2010). I use the interview portion of the CEX, based on quarter-yearly survey responses by "consumer units", which I call households. Income and socio-demographic characteristics are from the "consumer unit characteristics and income" files (FMLI). Expenditures are from the "monthly expenditures" files (MTBI), split by over 800 categories using universal classification codes (UCC)[6]. To allocate emissions, I link UCCs to sectors in the World Input-Output Database (WIOD). WIOD contains input-output linkages between 35 sectors in 40 countries as well as "Environmental Accounts" with greenhouse gas emissions by sector and country (Dietzenbacher et al., 2013; Timmer et al., 2015).

2.3.2 Calculating emissions intensities

I use the input-output portion of WIOD to attribute to each sector a total emissions intensity, the amount of CO_2 emissions from producing \$1 of output, taking into account

[6]The CEX Interview Survey provides a near complete picture of annual expenditures, including on larger items that are purchased more infrequently. It covers around 80-95 per cent of all household expenditures.

the full chain of inputs from other sectors ad infinitum. Following Leontief (1970), the key assumption is a linear relationship between sector outputs and required inputs (i.e. linear production function and constant returns to scale). In short, the vector of total emissions intensities (**e**) is the product of the emissions intensities of sectors (**d**) and the input-output structure (**T**) of the economy: $\mathbf{e} = \mathbf{T}'\mathbf{d}$.

This common accounting approach is described in Appendix B.1. The resulting total emissions intensity (CO_2/\$) is what I call technology—it takes into account both the direct emissions by sector k as well as the structure of the value chain (**T**) and emissions by input sectors (**d**). Emissions intensities may change for various reasons, including energy-saving innovation in production, but also changes in input structures or output prices. In sum, technology in this chapter refers to both production processes and input structures.

The CEX consumption categories (UCC) are allocated to sectors and emissions intensities. I follow where possible the matching procedure of Levinson and O'Brien (2019) to link UCC to IO codes by the Bureau of Economic Analysis[7]. Appendix Table B.1 lists the WIOD sectors and estimated emissions intensities in 1996 and 2009. Multiplying a household's expenditures ($c_{i,k}$) with the total emissions intensity of each category (e_k) yields an estimate of the CO_2 content of that household's consumption (y_i).

2.3.3 Limitations and refinements

I carry out multiple adjustments to ensure that I arrive at representative estimates of household carbon. First, I attribute emissions intensities to certain high-carbon goods directly. I do so for home electricity, heating oil, natural gas, gasoline for vehicles (incl. Diesel and motor oil), and air travel. For example, it is more precise to calculate directly the emissions content of \$100 spent on gasoline—based on gasoline prices and CO_2 content—than to attribute fuel expenditures to the average emissions intensity of the petroleum sector.

For this, I use data on retail prices for electricity, heating oil, natural gas, and gasoline from the U.S. Energy Information Administration (EIA, 2017). Emissions factors for gasoline, heating oil, natural gas, and kerosene are from the U.S. Environmental Protection Agency guidelines for the Greenhouse Gas Inventory (EPA, 2009). The emissions intensity of residential electricity is from the EPA's Emissions & Generation Resource Integrated Database (EPA, 2017). Appendix Table B.2 lists these direct

[7] I thank Arik Levinson and James O'Brien for kindly sharing their matching from UCC categories to IO codes used in their analysis and for answering my questions regarding their methodology. As there are many more UCC categories than IO sectors, the matching procedure applied by Levinson and O'Brien (2019) relies on a number of subjective judgements, which they outline in an online appendix to their paper.

emission factors. Using direct emission factors should significantly improve estimates. It raises average estimates of household carbon by 25% (from 25.0t to 31.0t in 2009).

Second, I account for global value chains and trade. This is important if the content of traded inputs into a sector is large and if households with different incomes consume goods with different import shares. I thus rely on the multi-region input-output (MRIO) tables included in WIOD to explicitly account for both global value chains and trade in final goods. To account for global value chains, I expand the input-output analysis described above to the 35 WIOD sectors and 41 countries (including "rest of the world"). This accounts for the emissions from foreign intermediate inputs. To account for final goods trade, I use WIOD information on "final consumption expenditure by private households" going to imports. I then calculate the emissions intensity of each sector as the average of domestic and foreign goods, weighted by their share in final consumption. The inclusion of global value chains raises average household emissions by about 7.4% in 2009 (from 31.0t to 33.3t), while the consideration of trade in final goods adds another 1.8% (from 33.3t to 33.9t).

Third, I account for greenhouse gases besides carbon dioxide (CO_2), in particular methane (CH_4) and nitrous oxide (N_2O). This is important if their relationship with income and consumption systematically differs from that of CO_2. I calculate a measure of total greenhouse gas emissions by converting CH_4 and N_2O to units of CO_2 equivalents (CO_2e)[8]. Including CH_4 and N_2O raises estimates of household greenhouse gas footprints by about 42% in 2009, with a slightly higher increase for low-income households. Details are provided in Appendix B.1.

With those refinements, I hope to obtain a comprehensive estimate of household carbon. Still, my approach is subject to the typical limitations of input-output analysis summarised by Wiedmann (2009). Importantly, I cannot account for the quality of goods within a sector. For example, \$5 spent on a premium organic loaf of bread are estimated to have five times the CO_2 content of \$1 spent on a mass-market loaf. If consumption of goods with higher price-per-CO_2 ratio is increasing with income, I may underestimate the concavity of EECs.

[8]I use the 100 year global warming potential multipliers with climate-carbon feedbacks as reported in the IPCC AR5 report (Myhre et al., 2013): 34 for CH_4 and 298 for N_2O.

2.3.4 Final sample

I supplement data on expenditures and estimated CO_2 with household characteristics taken from the FMLI interview files of CEX. Households are surveyed in five consecutive quarter-yearly interviews. There are thus different waves of households starting the survey each quarter of every year. To generate yearly cross-sections, I assign households to the year in which their second interview took place. I include only observations with data from all five interviews and classified as "complete income reporters". Only households with a positive reported after-tax income are included to avoid distortion from households declaring financial losses. Due to poor coverage of highest incomes, I limit the sample to households with real after-tax income below \$400K[9] (2009 USD). The final sample has 51,265 households, surveyed between 1996 and 2009. Table 2.1 provides summary statistics of key variables.

Table 2.1: Summary statistics

	N	mean	sd	min	max	Gini '09
Income before tax (k\$)	51,265	54.88	50.73	0.001	510.1	0.45
Income after tax (k\$)	51,265	51.86	47.09	0.001	389	0.44
Expenditure (k\$)	51,265	42.14	35.98	2.439	1,411	0.33
HH CO_2 (t, closed)	51,265	34.4	19.0	0.5	435.6	0.28
HH CO_2 (t, open)	51,265	36.9	21.0	0.6	479.5	0.28
HH CO_2 (t, open+trade)	51,265	37.6	21.5	0.7	517.4	0.29
HH CH_4 (kg, open+trade)	51,265	320.5	182.8	5.284	6,206	0.29
HH N_2O (kg, open+trade)	51,265	11.59	6.25	0.09	105.9	0.28
HH GHG (t CO_2e, op.+tr.)	51,265	51.9	29.0	0.9	760.0	0.28
Age (HH head)	51,265	51.63	16.85	15	94	
Family size	51,265	2.586	1.496	1	14	

Notes: Estimates for household emissions contained in consumption expenditure according to methodology described in text (using data from WIOD, EPA, EIA). All other variables from the US Consumer Expenditure Survey. Households with negative reported after-tax income and income above \$400K excluded. All calculations using CEX population weights (FINLWT21).

[9]Incomes are not top-coded, but it has been shown by Sabelhaus et al. (2013) that the very highest-income households have a lower survey response rate and are thus under-represented in the CEX. Limiting the sample to after tax incomes below \$400K results in dropping 85 observations (0.2%) of the total. I do not include households with imputed incomes.

2.4 Descriptive Environmental Engel curves

Following Levinson and O'Brien (2019), I construct parametric and nonparametric Environmental Engel curves (EECs) for household carbon. The advantage of the nonparametric approach is that it does not impose any functional form on EECs.

Figure 2.1 presents nonparametric estimates of carbon EECs in 1996 and 2009, respectively the first and last year of my sample. They show average after-tax incomes and household carbon at different income deciles. The CO_2 content includes emissions from global supply chain and imports of final goods ("open+trade"). A breakdown of household carbon in 2009 by major consumption categories and information on other greenhouse gases is in Appendix B.4. To avoid confusion with the more involved nonparametric smoothing techniques applied below, I shall call these "descriptive" EECs. Figure 2.1 suggests the following characteristics of consumption-based carbon:

1. EECs are increasing: Higher incomes are linked to more CO_2 contained in household consumption. For example, the emissions of the top decile in 1996 was over 3 times that of the bottom decile (over 70t compared to 21t). Embedded CO_2 is a normal good.

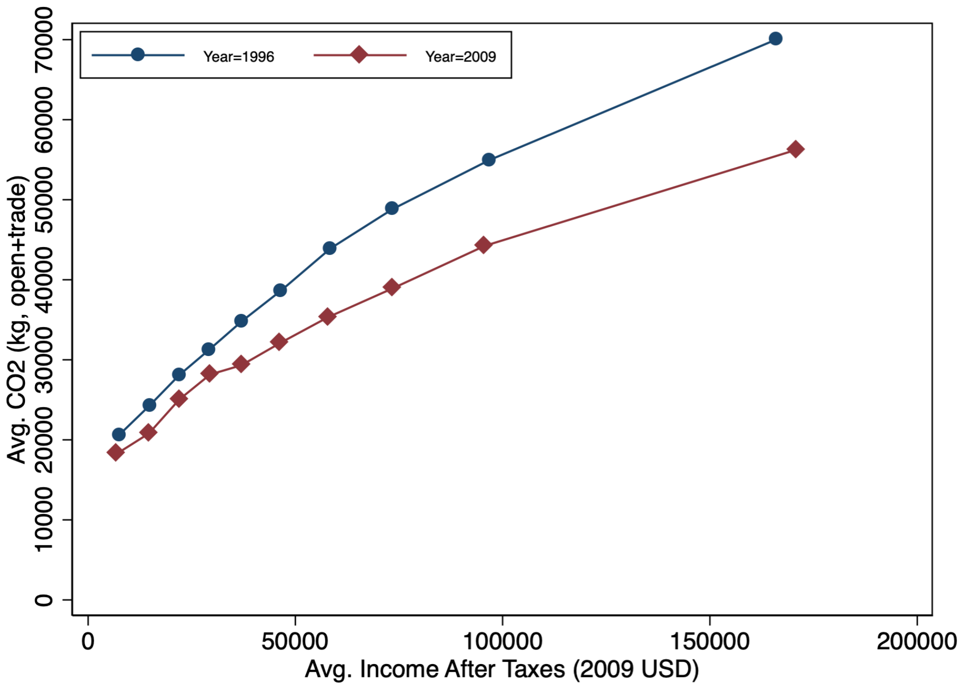
2. EECs are concave: Higher incomes are associated with less than proportionally more emissions, i.e. the carbon intensity of income (CO_2/\$) is decreasing. Embedded CO_2 behaves like a necessity.

3. EECs shift down over time: The average carbon-content of consumption decreases over time. For example, the average household carbon of top income deciles dropped by 20% between 1996 (70t) and 2009 (56t). Three effects might contribute to this shift:

   - Savings effect: Consumers spend less per dollar of income
   - Composition effect: Consumers are shifting to a less carbon-intensive mix
   - Technology effect: The carbon intensity (CO_2/\$) of output is decreasing

These observations are in line with those made by Levinson and O'Brien (2019) about EECs for air pollutants. My estimates of household carbon are also broadly in line with previous estimates. For example, Weber and Matthews (2008) estimate an average pollution intensity of aggregate consumption of 0.7 kg CO_2/\$ in the US in 2004. My aggregate average in 2005 is 0.82 kg CO_2/\$ (0.68 kg CO_2/\$ when using only WIOD-based emission factors).

Figure 2.1: Descriptive Environmental Engel curves - Household CO_2



Notes: Averages of household income after tax (2009 USD) and estimated CO_2-content of consumption (current technology), separately by year and income deciles. Household weights as provided by CEX sample. Households with negative reported after-tax income and income above $400K excluded.

2.4.1 Shifts of EECs over time: Technology, savings, composition

Over time, the evolution of aggregate emissions can be split into five dynamics: (1) aggregate income growth (scale), (2) changes in the distribution of income (distribution), (3) changes in expenditure levels per income (savings), (4) changes in the share of expenditure to different goods (composition), and (5) changes in emissions intensities of consumption (technology). Dynamics (1) and (2) represent movements along EECs, while (3), (4) and (5) represent shifts of the EECs. In this section, I focus on the latter.

I first show that technology is the most important driver of emissions over time. Had emissions intensities (CO_2/\$) remained unchanged, average household carbon would be significantly higher than at current technologies. This is shown in Figure 2.2, which compares the actual CO_2 content of the consumption of the average household (at current technologies) to hypothetical estimates assuming constant 1996/2009 technologies (i.e. carbon intensities). At constant technology, average household carbon would have increased by 53% between 1996 and 2009 (37.8t of CO_2 and 57.9t at 1996 technology). This increase would have been the combination of the other four dynamics—scale, distribution, savings, and composition. However, improvements in technology have outweighed these dynamics, and average household carbon has actually decreased by 10% (from 37.8t in 1996 to 33.9t in 2009). Put differently—comparing the grey (dashed) and black (solid) lines in Figure 2.2—emissions in 2009 would have been 70% higher with 1996 technology (57.9t instead of 33.9t). As discussed in Section 2.3, this perspective of technological change—as a drop in emissions intensity per $ of output—encompasses energy saving innovation in production processes, shifts in value chains towards less polluting inputs (including imports), and relative price increases of polluting goods[10].

Figure 2.2 depicts the strong impact of technology in driving down emissions over time. Figure 2.3 visually explores the role of the other drivers shifting EECs over time. The top left panel plots the EECs based on current technologies and real household income (2009 dollars). It is identical to Figure 2.1. In the top right panel, I instead hold emissions intensities (technology) constant at 1996 levels. Had technology not changed, EECs would have shifted upward. This shift—which together with income growth explains the 70% increase in Figure 2.2—is driven by changes in net savings and the composition of consumption. Spending ratios[11] appear to have increased somewhat, at least for lower incomes (bottom left panel). Households spent a higher portion

[10]For example, the observation that emissions would have been higher in 2008 at 2009 emission factors (blue line above dark grey line in 2008), may be driven by the strong decline in oil prices between 2008 and 2009, which resulted in an increase of emission factors for gasoline, heating fuel and natural gas.

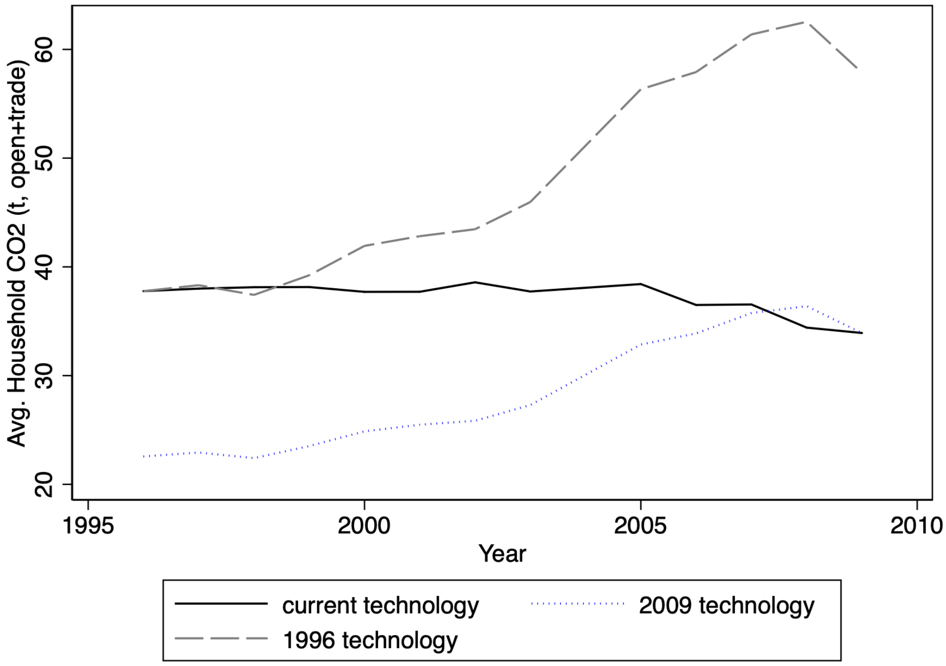
[11]It is important here to mention that throughout this chapter I refer to as expenditures/spending only as those expenditures that I have linked to WIOD sectors and thus to a carbon intensity. Significant portions of consumer spending that may be left out are for example the acquisition of housing via mortgages or debt-financed purchases of vehicles.

of their income in 2009. In addition, there has been a composition effect towards more pollution, even when holding technology constant (bottom right panel). Households across real income levels bought a more carbon-intensive mix of goods (CO_2 per $ expenditure) in 2009 than in 1996. Overall however, EECs shifted down (top left panel) because technology improvements[12] outweighed the savings and composition effects.

This visual inspection provides useful insights on what drove shifts in EECs, but it cannot capture movements along EECs due to income. Below, I use regression-based EECs for a systematic decomposition analysis, which can separate out the contribution of income.

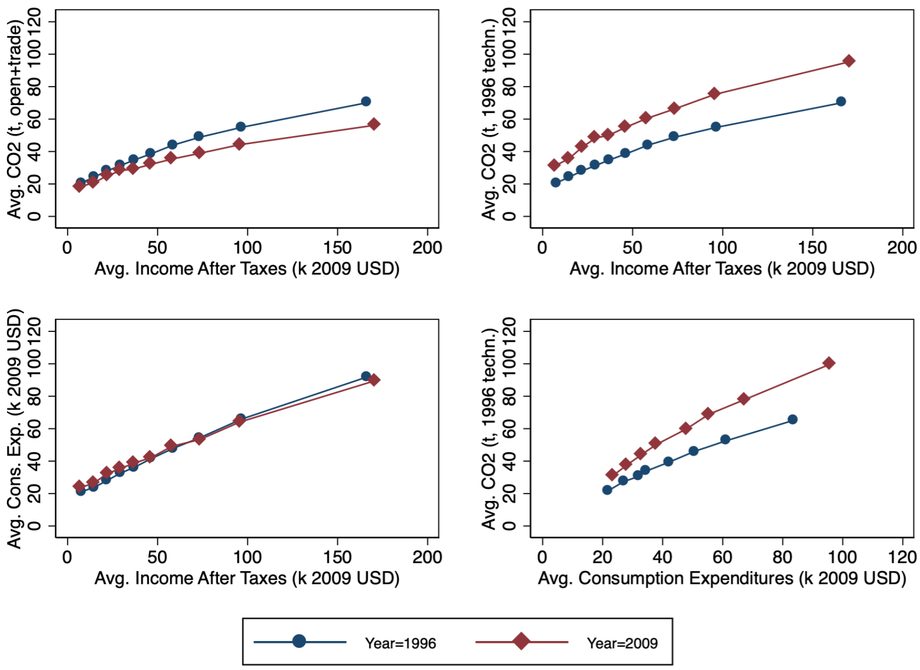
[12] The drop in emissions intensities is equally distributed across income groups. For each income decile the ratio of the actual carbon footprints in 2009 (top left) and 2009 footprints at 1996 emissions intensities (top right), is between 58-59%. The same is true for the change in the composition of consumption. The change in 2009 to 1996 CO_2 at constant technology (bottom right) is +52% for each decile.

Figure 2.2: The role of technology



Notes: Averages of estimated CO_2-content of consumption, by year. 'Current technology' refers to estimates pairing expenditures in a given year to the emissions intensities calculated for the same year; '1996 technology' refers to pairing expenditures from each year to emissions intensities of consumption categories in the year 1996; '2009 technology' refers to pairing expenditures from each year to emissions intensities of consumption categories in the year 2009. Household weights as provided in CEX sample. Households with negative reported after-tax income and income above $400K excluded.

Figure 2.3: Shifting EECs - Technology, savings and composition



Notes: Averages of household income after tax (current USD and constant 2009 USD), household consumption expenditure (2009 USD), and estimated CO_2-content of consumption, separately by year and income deciles. Top left panel is equivalent to Figure 2.1. Bottom left panel shows average total consumption expenditures. Top right and bottom right panels show household CO_2 at '1996 technology' (pairing expenditures from both 1996 and 2009 to emissions intensities of categories in 1996); Household weights as provided in CEX sample. Households with negative reported after-tax income and income above $400K excluded

2.5 Parametric Environmental Engel curves

In Section 2.4, descriptive EECs showed the unconditional relationship between household income and CO_2. But households may differ with respect to other characteristics related to consumption, including household size, education, and location (e.g. Buechs and Schnepf, 2013). To account for this, I estimate parametric EECs from the following linear model:

$$y_{it} = \beta_{1t} m_{it} + \beta_{2t} m_{it}^2 + \mathbf{x_{it}}' \boldsymbol{\delta_t} + \varepsilon_{it} \tag{2.4}$$

For each yearly cross-section t, I run a linear regression with consumption-based CO_2 emissions y_{it} of household i as the dependent variable. Independent variables include real after-tax household income m_{it}, its square, and a vector of household characteristics $\mathbf{x_{it}}$. These are family size, family size squared, age of household head, age of household head squared, binary marital status, race categories, educational attainment categories, and regions. At the end of this section, I show how that these quadratic EEC approximate well the fit of more flexible nonparametric approaches.

This approach does not presuppose a causal relationships, but simply accounts for partial linear associations. For example, educational attainment and income are clearly related in various ways. Estimating equation (2.4) identifies the partial association between income and consumption-based CO_2 emissions, holding constant educational attainment (and other characteristics). When using coefficient estimates to calculate the "equity-pollution dilemma" in Section 2.6, I thus quantify the dilemma for a short-term redistribution of income only, holding other household characteristics constant. More long-term, structural policies aimed at reducing inequality may also affect, or even target, education and other household characteristics. The unconditional association between income and pollution may then be informative in such instances. That is why I report results both with and without household controls.

2.5.1 Parametric (quadratic) Environmental Engel curves

Table 2.2 presents regression estimates of equation (2.4) for 1996 and 2009. EECs for household carbon are upward sloping ($\hat{\beta}_{1t} > 0$) and concave ($\hat{\beta}_{2t} < 0$), implying that CO_2 is a normal good that behaves like a necessity. For example, estimates in Column 4 suggest that an additional \$1000 in after-tax income is associated with a 210 kg increase in consumption-based CO_2 emissions for households with \$50K income (223–50 $\cdot$ 0.258), but only a 197 kg increase at an income of \$100K (223–100 $\cdot$ 0.258). The turning point of the EEC, after which additional income is associated with less emissions is at an income of \$870K in 2009. This is well above the sample range which covers incomes between 0 and \$400K. CO_2 is thus a normal good for the entire range of my sample.

While other household characteristics appear to be associated with household carbon, EECs are also concave after controlling for those (Columns 2 and 4). Differences in household carbon across income levels are not primarily due to other characteristics (e.g. education). Below, I show that the "equity-pollution dilemma" is proportional to the coefficient estimate for quadratic income $\hat{\beta}_{2t}$. Controlling for household characteristics thus reduces the estimated magnitude of the dilemma. In the short-run, while holding other characteristics constant, we face a smaller "equity-pollution dilemma". But as discussed above, when assessing the impact of long-run policies targeting inequality, the unconditional EECs might be more pertinent.

2.5.2 Movement along EECs: Income and expenditure

In Section 2.4, I showed that shifts of EECs were due to changes in technology (emissions intensities), net savings and the composition of consumption. As seen in Figure 2.3, the savings and composition effects pushed EECs up, while the technology effect pushed them down. The latter effect dominated and EECs shifted down (Figure 2.1). But as shown in Figure 2.2, aggregate emissions dropped less than the shift in EECs may suggest. Here, I quantify how much of the change in aggregate emissions between 1996 and 2009 can be attributed to movements along EECs—changes in average income levels as well as other household characteristics. To do so, I use Oaxaca-Blinder decomposition, which was initially suggested to decompose wage differentials between population groups (Oaxaca, 1973; Blinder, 1973).

As shown in Figure 2.2, average household carbon at constant 2009 technology increased by 50% between 1996 and 2009 (from 22.6t to 33.9t). Table 2.3 displays results of an Oaxaca-Blinder decomposition based on regression estimates in Table 2.2. Essentially, the 11.3t increase in average CO_2 is divided into (i) changes in average income and household characteristics assuming constant regression coefficients (i.e. maintaining the original EEC), (ii) changes in regression coefficients holding variable levels constant (i.e. EECs that shift for reasons other than technology), and (iii) an interaction thereof. The method is further detailed in Appendix B.2 and the summary by Fortin et al. (2011).

Table 2.3 Column 1 shows that changes in (i) average income after tax (scale), essentially movement along EECs, account for about 35% of the change in household carbon between 1996 and 2009 (3.9t out of the 11.3t). Changes in other household characteristics contribute little (0.4t). Meanwhile, shifts of EECs, effects (ii) and (iii), account for about 60% (7.0t) of the difference. Sometimes, total expenditure is seen as a more appropriate and less volatile measure for lifetime income than is annual income. Using total consumption expenditure instead of annual after-tax income—essentially merging the 'scale' and 'savings' channels—these account for 60% of the

Table 2.2: Parametric estimates of quadratic EECs (1996 / 2009)

	1996		2009	
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
Income (k USD, after tax)	**597.54*****	**397.39*****	**333.674*****	**223.19*****
	(30.6475)	(33.8508)	(12.5338)	(13.3885)
Income squared	**-1.26*****	**-0.57****	**-0.54*****	**-0.26*****
	(0.24)	(0.25)	(0.06)	(0.06)
Family size		7,224.71***		6,045.75***
		(721.24)		(640.50)
Family size squared		-531.37***		-390.45***
		(96.72)		(89.32)
Age of HH head		882.97***		602.85***
		(83.60)		(68.30)
Age squared		-7.22***		-4.57***
		(0.78)		(0.62)
Married (binary)		3,017.72***		3,498.02***
		(727.40)		(516.92)
Race (Black)		-4,538.61***		-2,222.66***
		(833.76)		(625.63)
—(Native American)		-4,061.46***		-3,850.20
		(1,517.42)		(2,381.08)
—(Asian / Pacific)		-6,459.37***		-3,523.86***
		(1,242.53)		(1,202.15)
—(Pacific Islander)				-5,189.48**
				(2,595.38)
—(Multi-race)				3,073.65
				(2,920.37)
Education (below HS)		1,543.11**		1,527.98**
		(758.24)		(595.57)
—(high school)		3,874.11***		3,552.08***
		(804.19)		(612.26)
—(some college/vocational)		4,583.58***		3,130.91***
		(979.16)		(743.73)
—(college degree or higher)		3,360.63**		3,048.08***
		(1,425.79)		(1,113.49)
Region (Midwest)		-147.87		-2,074.28***
		(792.33)		(631.21)
—(South)		1,582.21**		-499.46
		(800.76)		(604.03)
—(West)		-1,986.63**		-2,938.68***
		(846.83)		(682.12)
Constant	18,110***	-17,674***	17,360***	-10,358***
	(686.57)	(2,350.55)	(446.19)	(2,047.46)
Observations	3,069	3,069	4,407	4,378
R-squared	0.45	0.55	0.40	0.51

Notes: Estimates from OLS regression of equation (2.4). Each time the dependent variable is household emissions contained in consumption expenditure, calculated according to methodology described in text (using data from WIOD, EPA, EIA). All other variables from the US Consumer Expenditure Survey. Household weights as provided in CEX sample. Households with negative reported after-tax income and income above $400K excluded. Heteroskedasticity-robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.3: Changing CO_2 over time (1996 vs. 2009)

	(1) Income	(2) Expenditure
Income after tax	4.9*	
Income squared	-1.0*	
Expenditure		7.7*
Expenditure squared		-0.8*
Family size	-0.1	0
Family size squared	0.1	0
Age	1.0*	0.8*
Age squared	-0.7*	-0.6*
Married	0	0
Race dummies	0	0
Education dummies	0.1*	0
Regional dummies	-0.1*	-0.1*
Total chg. due to income (movement along EECs)	**3.9**	
Total chg. due to expenditure		**6.9**
Total chg. due to other demographics	**0.4**	**0.2**
Unexplained difference (shift in EECs)	**7.0**	**4.4**

Notes: Estimates based on Oaxaca-Blinder decomposition for factors contributing to average changes in household carbon between 1996 and 2009. Movement along EECs in column 1 is calculated as coefficient estimates from regression model (Table 2.1, Column 2) multiplied by difference by corresponding changes in variable levels. Column 2 is constructed in parallel fashion but replacing after-tax income with aggregate consumption expenditure in the regression and decomposition. CO_2 content is estimated based on method described in Section 2.3, using CEX, WIOD, EPA, EIA data. Household weights as provided by CEX survey. Households with negative reported after-tax income and income above $400K excluded. * $p < 0.05$.

overall change in household carbon (6.9t out of 11.3t). Meanwhile, shifts of EECs, due to a change in the composition of consumption at a given expenditure level, account for about 35% (3.9t out of 11.3t). As shown in Figure 2.2, improvements in technology outweigh these dynamics, and average household carbon at current technology has actually decreased by 10% (from 37.8t to 33.9t).

In sum, my findings suggest that technology is the most important driver of changes in average carbon emissions over time. But movements along EECs—due to income growth—also significantly drive changes in household carbon. For the rest of this chapter, I focus on the distribution of incomes and emissions across households in one time period.

2.5.3 Decomposing carbon inequality

In Figure 2.4, I plot Lorenz curves for after-tax incomes and household carbon in 2009. Larger deviations from the 45-degree line represent higher inequality. Incomes were more unevenly distributed than household carbon (Gini of 0.44 and 0.29 respectively). Moreover, income inequality is a key driver of inequality in household carbon. The blue (dotted) line shows CO_2 levels predicted based on a regression with only income (Table 2.2, Column 3), while the orange (dashed) line shows actual household carbon. The distribution of income alone can explain a large share of household carbon inequality (Gini of 0.22 and 0.29 respectively).

We also see this using a more systematic method of quantifying the contribution of income to the dispersion of household CO_2, again using estimates from Table 2.2. I follow the regression-based approach by Fields (2003), building on factor decomposition initiated by Shorrocks (1982). The method is detailed in Appendix B.3. It was previously applied to inequality in CO_2 emissions per capita between countries (Duro et al., 2017). I apply it to inequality of household carbon within the United States.

Results in Table 2.4 show that income is the key driver of household carbon inequality. In 2009, the dispersion in after-tax income accounts for about 31-40% of the dispersion of CO_2 (Columns 3 and 4)[13]. In 1996, income even explains 34-45%. Family size is the second most important factor, accounting for about 13% and 12% in 1996 and 2009 respectively. Table 2.4 also suggests that there is a significant portion of the dispersion in CO_2, which is not accounted for by income or other variables. Residual dispersion is 45% and 49% in 1996 and 2009 respectively. This suggests a significant role for household heterogeneity in preferences or unobserved characteristics not included in equation (2.4).

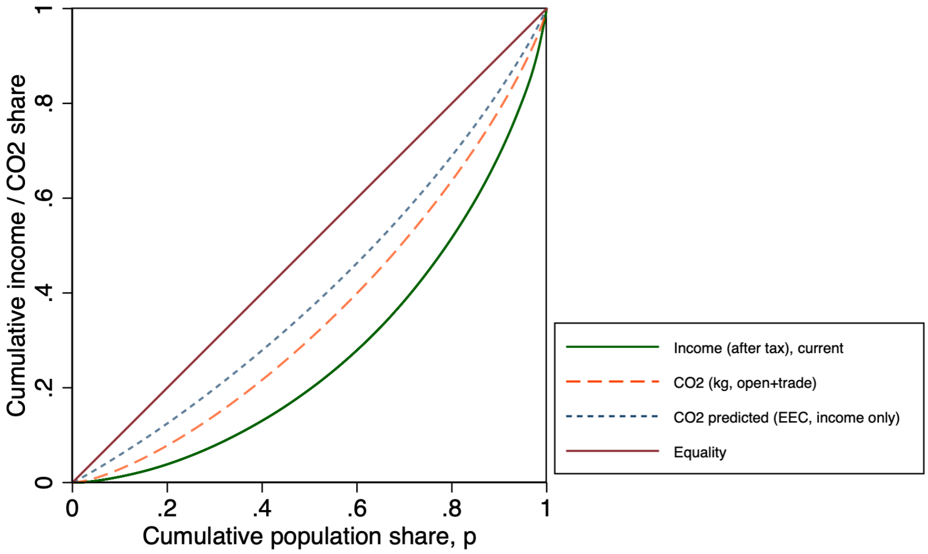
[13]It is possible that other measures of economic inequality—such as measures of wealth or lifetime income—explain even larger fractions of the variation in household carbon.

Table 2.4: Decomposition of household carbon inequality (1996 / 2009)

	(1) 1996 (income)	(2) 1996 (full)	(3) 2009 (income)	(4) 2009 (full)
Income after tax	0.642	0.427	0.606	0.407
Income (squared)	-0.192	-0.0861	-0.204	-0.0984
Famiy size		0.215		0.207
Family size (squared)		-0.0889		-0.0773
Age		-0.0902		-0.0597
Age (squared)		0.112		0.0686
Married		0.0327		0.0407
Race (sum)		0.012		0.004
Education (sum)		0.018		0.012
Region (sum)		0.001		0.002
Residual	0.55	0.448	0.598	0.494
Observations	3,069	3,069	4,407	4,378
Total contribution of income	**45%**	**34%**	**40%**	**31%**
Total contribution of other demographics	**NA**	**21%**	**NA**	**20%**
Unexplained (residual)	**55%**	**45%**	**60%**	**49%**

Notes: Inequality decomposition based on coefficient estimates from linear regression models (Table 2.2). Calculations made using Stata module INEQRBD by Fiorio and Jenkins (2007). Household weights as provided in CEX sample. Households with negative reported after-tax income and income above $400K excluded.

Figure 2.4: Lorenz curves - Income and household carbon (2009)



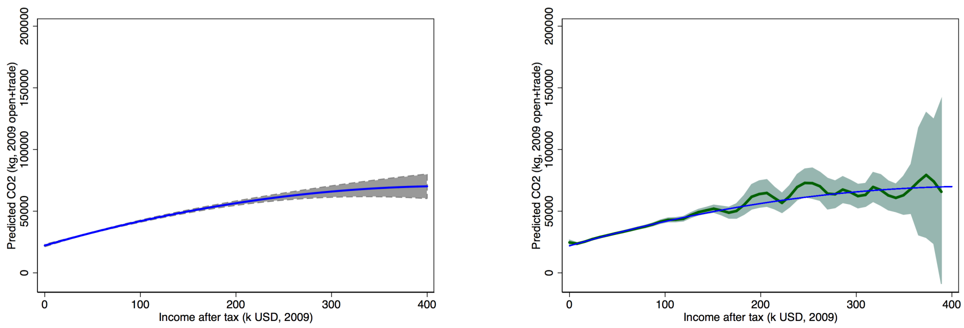
Notes: Cumulative population share and cumulative values of after-tax income (current USD), estimated household carbon contained in consumption (kg) and predicted values based on linear regression model with income and its square as independent variables. Household weights as provided by CEX sample. Households with negative reported after-tax income and income above $400K excluded.

2.5.4 Robustness: Quadratic vs. nonparametric fit

The above results rely on estimates of EECs which include a squared income term. This is a common ad hoc procedure when nonlinear relationships with income are suspected. Here, I compare equation (2.4) to more flexible semiparametric specifications, fitting a Gaussian kernel weighted local polynomial for income while linearly controlling for other covariates[14]. The fitted values of the quadratic specification (Figure 2.5a) are very similar to the more flexible semiparametric one (Figure 2.5b). This is confirmed by an equivalence test as proposed by Hardle and Mammen (1993). For each polynomial degree, we test the null hypothesis that the adjustment of degree $n+1$ is appropriate. We are looking for the lowest degree of polynomial for which we fail to reject this null. Table 2.5 shows that this is the case for the quadratic model in 2009. Quadratic EECs are not only convenient, they also capture most of the income-CO_2 relationship. As I show next, they also yield a simple formula for the "equity-pollution dilemma".

Figure 2.5: Environmental Engel curves - CO_2 (2009)

(a) Quadratic fit **(b)** Nonparametric fit



Notes: (a) Blue = fitted values of quadratic model of equation (2.4), holding other covariates constant at mean; Grey = 95% confidence intervals from Huber-White heteroscedasticity-robust standard errors. (b) Green = fitted values of semiparametric model, equivalent to (2.4) but with a nonparametric fit for income (m); Green = 95% confidence intervals; Blue = fitted values of quadratic model (2.4)

Table 2.5: Goodness of fit - Nonparametric vs. polynomial (2009)

Polynomial degree tested	0 None	1 Linear	2 Quadratic	3 Cubic	4 Quartic
T test (standardised)	26.395***	1.911*	0.792	0.77	0.596
[p value]	[0.00]	[0.09]	[0.73]	[0.84]	[0.97]

Notes: Hardle and Mammen (1993) test for goodness of fit of polynomial adjustment for equation (2.4) with different polynomial degrees for annual after-tax income by column. Dependent variable is household carbon footprint in 2009 calculated as described in Section 2.3. Covariates as in Tables 2.2-2.4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[14]The specification includes as linear covariates: family size, family size (squared), age of HH head, age (squared), marital status, education, race, region. Estimates are from the Stata module SEMIPAR, which estimates the Robinson (1988) double residual estimator.

2.6 The "equity-pollution dilemma"

Above, I have used Environmental Engel curves (EECs) to show that income is an important driver of CO_2 emissions over time as well as their distribution across households. I have shown that carbon EECs are upward-sloping and concave. This concavity suggests an *"equity-pollution dilemma"—progressive income redistribution may raise aggregate emissions from consumption.* Simply put, the propensity to generate emissions from an additional unit of income is higher at lower incomes. While this dilemma has been acknowledged (Scruggs, 1998) and assessed using aggregate data (Heerink et al., 2001), it has yet to be quantified. I propose a method to do so using quadratic EECs estimated from consumption micro-data.

2.6.1 Quantifying the "equity-pollution dilemma"

I have shown that quadratic EECs approximate well the relationship between income and household carbon, even after controlling for covariates. This quadratic specification yields a simple formula for the "equity-pollution dilemma". We assume that households have homogenous preferences and move in parallel to the EECs when their incomes change (at least conditional on the covariates). A marginal transfer from household j to household i then changes total consumption-based CO_2 emissions as follows:

$$\frac{\partial y_i}{\partial m_i} - \frac{\partial y_j}{\partial m_j} = -2\beta_2 \left(m_j - m_i\right) \tag{2.5}$$

This leaves us with a useful result to quantify the "equity-pollution dilemma": *The expected change in aggregate emissions, when choosing at random two households from the population, and re-distributing a small amount of income from the richer to the poorer, is a function of the curvature of EECs (coefficient estimate $\hat{\beta}_2$) and Gini's mean difference Ψ (GMD), giving*

$$\begin{gathered} E_{ij}\left(\frac{\partial y_i}{\partial m_i} - \frac{\partial y_j}{\partial m_j}|m_j > m_i\right) = -2\hat{\beta}_2 E_{ij}\left(m_j - m_i|m_j > m_i\right) = -2\hat{\beta}_2 \Psi\left(F(m)\right) \\ \text{where } \Psi\left(F(m)\right) = \int\int |y-z| dF(y) dF(z). \end{gathered} \tag{2.6}$$

The expected change in aggregate emissions is negatively proportional to $\hat{\beta}_2$ as well as the dispersion measure Ψ.[15] The more dispersed the distribution of incomes (larger Ψ) and the more concave the EECs (larger $-\hat{\beta}_2$), the larger is the "equity-pollution dilemma".

In 2009, values of $\Psi = 55.3$ (in k USD) and $\hat{\beta}_2 = -0.26$ give an expected increase

[15]The discrete version of GMD can be defined as $\Psi = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1}^{N} |m_i - m_j| \; \forall \; i \neq j$.

of about 28.5 kg of household CO_2 for a marginal redistribution of \$1000 from a higher income to a lower income household (both drawn at random). That is a 5.1% increase above the average emissions related to \$1000 of income (514 kg). Table 2.6 lists regression coefficient estimates and the implied magnitudes of the "equity-pollution dilemma" for different greenhouse gases in 2009. Column 1 reproduces estimates of Table 2.2 Column 4 as well as the above calculation. Columns 2-4 list estimates for total greenhouse gases (CO_2e), methane (CH_4), and nitrous oxide (N_2O) respectively. For all of these, I estimate concave EECs and hence a positive "equity-pollution dilemma". However, the dilemma is largest for CO_2, with a rise in pollution from a marginal redistribution of 4.2% and 2.8% for CH_4 and N_2O respectively.

Table 2.6: The "equity-pollution dilemma" - Comparison of pollutants (2009)

	(1) CO2	(2) CO2e	(3) CH4	(4) N2O
Income (k USD, after tax)	223.187***	304.581***	1.996***	0.045***
	(13.3885)	(18.3258)	(0.1285)	(0.004)
Income squared (k USD, after tax)	-0.258***	-0.336***	-0.002***	-0.000***
	(0.0571)	(0.0785)	(0.0006)	(0.0000)
Observations	4,378	4,378	4,378	4,378
R-squared	0.506	0.525	0.506	0.476
HH characteristics	YES	YES	YES	YES
Implied "equity-pollution dilemma"				
Avg. emissions per income (kg per k USD)	563.3	789.9	5.186	0.169
$-2\hat{\beta}_2\Psi$	28.55	37.23	0.214	0.0047
Marginal effect of redistribution	**5.1%**	**4.8%**	**4.2%**	**2.8%**
Effect of full redistribution	2.3%	2.1%	1.8%	1.3%

Notes: Top panel shows OLS estimates for after-tax annual income and income squared from regression equation (2.4) where the dependent variable is a measure of household emissions footprints in 2009, CO_2, CO_2e, CH_4 and N_2O respectively. These are calculated as discussed in Section 2.3. Household covariates as in Tables 2.2-2.4. Bottom panel shows calculation of the effect of redistributing \$1000 in income progressively between two households randomly drawn from the income distribution. This is a function of the regression coefficient on squared income (top panel) and the Gini's Mean Distance income dispersion measure. Household weights as provided in CEX sample. Households with negative reported after-tax income and income above \$400K excluded. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.6.2 Full redistribution

I also predict the change in household carbon if all households had the same, mean income. *The difference between the expected mean of household carbon under "full equality" and the current mean level at a given income distribution is given by:*

$$\hat{\beta}_2 \left[\overline{m}^2 - \frac{1}{N} \sum_{i=1}^{N} (m_i)^2 \right] \tag{2.7}$$

In the case of my sample, average household carbon in 2009 is predicted to increase by 2.3% when moving to full income equality (from 33.9t to 34.7t). The respective values are 1.8% for CH_4 and 1.3% for N_2O. Estimates of the "equity-pollution dilemma" are sensitive to values of $\hat{\beta}_2$. As discussed above, these estimates quantify the effect of re-distributing income while holding other households characteristics (e.g. education) constant. Without covariates (Table 2.3, Column 3), I estimate a larger absolute $\hat{\beta}_2$ (0.54 instead of 0.26) and thus a larger dilemma.

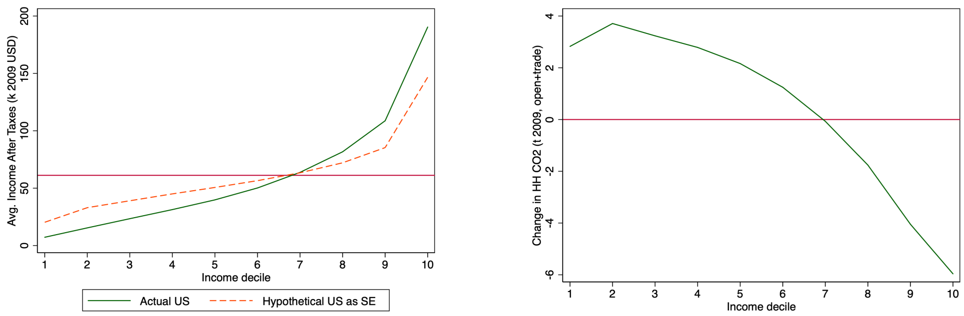
2.6.3 Hypothetical income distribution: Sweden

Besides full redistribution, I estimate as a more realistic scenario the predicted change in average household carbon when moving to the income distribution of Sweden. I obtain decile average household incomes in 2009 (disposable income including capital income, equalised) from Statistics Sweden (SCB, 2017). I then scale decile average incomes in the United States to replicate decile shares in Sweden. To exclude scale effects, I rescale incomes to keep constant mean income in the United States. Figure 2.6a compares hypothetical average decile incomes (red) to actual values in 2009 (green).

I then estimate the predicted change in CO_2 when moving to the hypothetical Swedish income distribution. Again, this is based on estimates from my preferred EEC specification (Table 2.2, Column 4). I predict that average household carbon would have been about 1.5% higher under the Swedish income distribution (34.4t instead of 33.9t). Figure 2.6b shows how this predicted increase is distributed across income deciles. The increase of emissions by lower income households outweighs the decrease in emissions by those at the top.

Figure 2.6: Hypothetical income distribution - Sweden (2009)

(a) Comparison of HH incomes **(b)** Predicted change in HH carbon



Notes: (a) Green = Average household income after taxes as observed in US CEX sample; Green = Average household income after scaling of US distribution to mirror decile shares of Swedish distribution of disposable household income. Both by income deciles, 2009 data. (b) Predicted difference between average household CO_2 by income decile between hypothetical distribution emulating Sweden and actual distribution in the United States. Calculations based on estimates reported in Table 2.2, Column 4. 2009 data.

2.6.4 Assumptions and limitations

My method of quantifying the "equity-pollution dilemma" relies on a number of assumptions. First, I assume throughout that I arrive at unbiased estimates of household carbon along the income distribution. One important concern is the emissions intensity (CO_2/\$) of goods from a certain sector may vary with income. As discussed above, price/quality heterogeneity of products likely means that we are underestimating $-\hat{\beta}_2$ and consequently the "equity-pollution dilemma". Second, I assume throughout that the linear, quadratic EECs specified in equation (2.4) are adequate. I have shown above that a second-degree polynomial specification approximates well the relationship between income and household carbon as shown by more flexible nonparametric models.

Third, I assume homogeneity of household preferences conditional on the set of household characteristics included in (2.4). I expect that households will respond to a change in their income by moving in parallel to the estimated EECs. This implies that there is no variable omitted from our specification of EECs that influences both incomes and consumption preferences at the same time. For example, Lewbel and Pendakur (2017) find evidence of significant preference heterogeneity in the demand for energy. Such unobserved heterogeneity in preferences would pose a problem for our quantification of the "equity-pollution dilemma" if it was correlated with income. Alan et al. (2018) also find evidence of such co-dependence between income and preferences. This may bias my estimate of the "equity-pollution dilemma". But I am not aware of evidence to predict the sign of such a bias.

Finally, my analysis is of partial equilibrium nature, assuming that external circumstance of consumption remain unchanged when income is redistributed. In particular, I assume fixed emissions intensities of goods, implying no change in production technologies, value chains or retail prices. I also assume that household consumption is independent of the income distribution and the consumption of others. There is no room for social or other-regarding preferences (Akerlof, 1997; Sobel, 2005), such as the desire for status discussed in Chapter 3. These assumptions appear less restrictive when considering marginal or small-scale redistribution of income. Large-scale redistribution may well lead to structural changes in the economy, which feed back into technologies, prices, and consumption. As discussed above, structural policies aimed at reducing inequality may also impact the distribution of other household characteristics such as education.

2.7 Conclusion

In this chapter I contribute to the understanding of the interplay between income inequality and the carbon content of consumption. I estimate Environmental Engel Curves (EECs), which describe household carbon along the income distribution. I find carbon EECs in the United States to be upward-sloping, concave, and shifting down over time. They are approximated well by a second-degree polynomial, controlling for household characteristics.

Over time I find that technology and income are both key drivers of changes in average household carbon, working in opposite directions. While average household carbon has declined by 10% between 1996 and 2009, it would have risen by about 50% had technology remained unchanged. Decomposition analysis based on EECs suggests that average income growth—movement along EECs—accounts for about 35% (and expenditure for up to 60%) of this increase at constant technology. In 2009, the distribution of incomes can also explain a large share (ca. 31-40%) of the distribution of carbon footprints.

I then focus on the relationship between income inequality and aggregate CO_2 emissions. A key contribution of this chapter is the quantification of the "equity-pollution dilemma" from micro-data using estimates of quadratic EECs. I estimate that a marginal transfer of $1000 from a richer to a poorer household in 2009 may increase the CO_2 content of that income by 5.1% or 28.5kg. Emissions would have been 1.5% higher if income in the U.S. had been distributed as in Sweden and 2.3% higher under full equality.

The finding of a potential trade-off between income redistribution and carbon emissions may have important consequences for redistributive policies. However, the "equity-pollution dilemma" does not necessarily render income redistribution undesirable. The optimal degree of redistributive policy requires extensive welfare economic analysis and will rely on a variety of assumptions regarding market structure, household welfare and socially desirable outcomes. For example, the estimated increase of 28.5 kg in CO_2 emissions from a marginal redistribution of $1000 would equal a social external cost of 90 cents under a conservative estimate for the social cost of carbon of $31 (following Nordhaus, 2017). An inequality-averse social planner might well find that the benefits of redistributing $1000 of after-tax income outweigh this additional social cost of 90 cents. I hope that the proposed method to quantify the "equity-pollution dilemma" proves helpful for further work on this inequality-pollution relationship and its implications for public policy.

Chapter 3

Inequality and Positional Consumption: A Reference-dependent View

In this chapter I investigate the relationship between income inequality and the degree of status-seeking by consumers. I propose a stylised model of status-seeking, in which individual consumption of a positional good depends positively on a reference level shaped by peer consumption. I find that a unique equilibrium in such an economy exists under plausible assumptions about demand functions. I then assess the impact of changes in the income distribution on aggregate demand for the positional good. My approach takes into account the shape of Engel curves—the relationship between income and demand—which by themselves suggest an association between inequality and aggregate demand. When the reference level is the simple mean of consumption, status-seeking will act as a multiplier effect—we can predict the direction of change in aggregate demand from the shape of Engel curves under the previous equilibrium, but we will underestimate the magnitude of this shift. Using household expenditure data in the United States, I find concave Engel curves for "visible" consumption. This suggests a negative relationship between inequality and demand for status goods. The comparative statics are more complex when the reference level instead puts unequal weight on consumers. Despite concave Engel curves, inequality may result in higher demand for status goods when the status-relevance of consumers is increasing with income.

3.1 Introduction

Are concerns with social status amplified by inequality? Do individuals living in unequal societies invest more resources—money, effort and time—to establish and maintain their relative status? Such claims are sometimes made in popular writing (Roberts, 2011) as well as other fields of social science (Christen and Morgan, 2005; Wilkinson and Pickett, 2010). Meanwhile, the empirical evidence on this relationship is mixed and economic theory tends to predict the opposite (Bowles and Park, 2005; Hopkins and Kornienko, 2009; Charles et al., 2009). In this chapter, I investigate formally the conditions for a systematic relationship between inequality and status-seeking when status is based on a consumption reference level, and I consider the implications of this for the environment.

Under classical theories of demand, the preferences of an individual consumer are assumed to be exogenously given. Consumption choices depend only on the prices of goods and the budgets available to individual consumers. The distribution of income influences aggregate consumption primarily via the latter. The relationship between income inequality and aggregate demand is then determined by the shape of demand schedules that describe the relationship between individual income and demand—so-called Engel curves. However, recent models of consumer behaviour point to another channel through which the income distribution may shape consumption levels—other-regarding preferences. Each consumer may be influenced by the observed consumption of others. This suggests that the distribution of income will not only shape aggregate demand via changes to individual budgets, but also via peer-effects between consumers.

In this chapter I model an economy where consumers have status-seeking preferences based on a reference level. To facilitate the analysis, I propose a formulation of status-seeking based on the following dynamic: the demand of consumer i for a positional good, x_i, responds positively to a common reference level of consumption r, which in turn is shaped by the consumption of x by all consumers. Equilibria of such a system are those levels of consumption which individually respond to a reference level and in aggregate reproduce said reference level. I demonstrate for a general class of demand functions that such an equilibrium exists and is unique under weak assumptions. The proposed formulation of status-seeking is general enough to encompass a number of more ad-hoc models and reference levels proposed in previous contributions. While I model consumption as depending on a reference level, it is not necessary that consumers consciously consider such a reference level. Behaviour equivalent to following a reference level may result from less cognitively tasking frameworks. As an example, I show that pairwise interaction with random peers can generate behaviour that is equivalent to following a reference level. To do so, I reappropriate the canonical model of reference-dependence in decision making under uncertainty (Koszegi and Rabin, 2006, 2007). Depending on the degree of loss aversion, such a model of pairwise comparison nests two common types of status-seeking models—those of the "Keeping Up with the Joneses" variety, where the economy-wide mean serves as the reference level, and those where consumers are "upward-looking", comparing themselves only to those with higher incomes.

I then assess how changes in the distribution of income may impact aggregate demand for positional goods in the presence of status-seeking. In particular, I ask if and under what conditions aggregate positional consumption responds in a predictable fashion to any mean-preserving transfer. These are the conditions under which we may reasonably claim a systematic relationship between the degree of income inequality and the degree of status-seeking consumption in a society.

I show that when the reference level is the simple mean of positional consumption $\bar{x}$, status-seeking will amplify the comparative statics implied by the curvature of static Engel curves (at a given equilibrium reference level). Put differently, status-seeking then works like a multiplier effect. Combining household expenditure data from the United States Consumer Expenditure Survey with measures of the "visibility" of different goods (from Heffetz, 2011), I find that Engel curves for visible goods are concave—suggesting that more income inequality results in less aggregate demand for these goods. When the reference level is instead a weighted mean, giving differentiated weight to the positional consumption levels of different consumers, a reversal of implied comparative statics is possible under conditions that I derive. More generally, I show that it becomes an impossibility to derive a general rule on how inequality may influence status-seeking unless the weight of individual consumers in the reference level is monotonic with income.

This work is motivated by the mixed evidence on the relationship between inequality and status-seeking. On the one hand, there is growing empirical evidence suggesting that higher levels of income inequality are associated with higher aggregate demand for status goods (Charles et al., 2009; Frank et al., 2014; Betrand and Morse, 2016). This evidence is in line with the claims mentioned above. At the same time, existing models of status-seeking often predict the opposite—an intensification of status-seeking as income inequality falls (Hopkins and Kornienko, 2004, 2009). Again, there are empirical contributions that support a negative association between inequality and consumption of status goods in the United States (Hwang and Lee, 2017) and India (Roychowdhury, 2017). By proposing an alternative model of positional consumption based on a consumption reference level, and by incorporating empirical evidence on household expenditure patterns, I contribute to this open debate.

Previous analyses of status-seeking largely ignore the possibility that demand for positional goods may vary with income for reasons other than their positionality. In one popular class of such models, positional consumption takes the form of a costly signal without intrinsic "use value" (Hopkins and Kornienko, 2004, 2009; Bilancini and Boncinelli, 2012). In contrast, the formulation of status-seeking proposed in this chapter makes it possible to analyse status-seeking in interaction with other drivers of demand by allowing demand to be a joint function of income and a reference level. Despite this richness, I do not find that the shape of Engel curves, which appear concave, can by itself explain a positive association between inequality and status-seeking. Still, and despite concave Engel curves, I find that status-seeking may increase with inequality if the weight of consumers in the reference level is increasing with income to a sufficient degree.

The question of how income redistribution may influence the demand for positional consumption has important implications for the relationship between income inequality and the environmental burden of consumption, which is the broader theme of this PhD thesis. It has previously been noted that the emission intensity of consumption tends to be decreasing with income as visualised by concave "Environmental Engel Curves" (EECs) depicting the pollution content of consumption for households at different positions in the income distribution (e.g. Levinson and O'Brien, 2019). In Chapter 2 of this thesis, I show how the observation of concave EECs for CO_2 in the United States might suggest an "equity-pollution dilemma", where progressive income redistribution results in higher aggregate emissions. In this chapter I investigate if it is possible that such status feedback dynamics overturn the comparative statics implied by static Engel curves. While the empirical evidence from household expenditure patterns does not support such a reversal of the "equity-pollution dilemma", my theoretical results show that it is at least possible.

This chapter proceeds as follows. Section 3.2 briefly reviews the previous literature. Section 3.3 provides suggestive evidence on the demand for status goods across different income groups in the United States. Section 3.4 presents the model of status consumption based on a reference level and derives conditions for existence and uniqueness of equilibria. Section 3.5 derives comparative statics with respect to income transfers. Section 3.6 discusses the implications of the findings for the environmental burden of consumption. Section 3.7 concludes.

3.2 Previous literature

The idea that economic agents may be motivated by their relative position in the economy was noted as early as in the work of classical economists such as Smith (1838) and Marx (1849). Veblen (1899) proposed the idea of *conspicuous consumption* motivated by imitating and/or differentiating oneself from a certain reference group. This was followed by the *relative income hypothesis* by Duesenberry (1949) and his proposition to include into an individual's utility function the income level of others. Recently, there has been a revival of the analysis of relativist motivations of economic behaviour as evidenced by the growing literature on *social* and *other-regarding preferences* (Akerlof, 1997; Sobel, 2005). This development is in parallel to a broader revival of theories of endogenous preferences (Wildavsky, 1987; Bowles, 1998), where individual behaviour is shaped by social feedback mechanisms, such as norms and institutions (e.g. Bowles, 1998; Sobel, 2005; Young, 2015). Status-seeking consumption is one such feedback mechanism.

3.2.1 Status-seeking consumption

A growing empirical literature points to systematic increases in the demand for goods that are considered "visible" (Charles et al., 2009; Heffetz, 2011) as the income of a relevant peer group rises. In developing countries, individuals have been observed to increase their expenditures on certain positional goods in response to their neighbours receiving cash transfers (Roth, 2014; Boneva, 2015). Similarly, Kuhn et al. (2011) observed a significant increase of expenditure on cars by Dutch households after one of their neighbours had won a new car in the lottery[1].

Following suggestions by Hirsch (1976), it was Frank (1985a) who first proposed to model consumer choice as depending on status, based on the relative consumption level of so-called *positional goods*[2]. Much of the theoretical literature incorporates variations of the initial model by Frank (1985b), who proposed the following utility-based formalisation of status preferences for a consumer choosing between two goods, one positional (x) and affecting status (S), the other non-positional (y):

$$U = U\left(x, y, S\left(x\right)\right) \tag{3.1}$$

Common assumptions are that status is desirable ($\frac{\partial U}{\partial S} > 0$), increasing in one's own consumption of the positional good ($\frac{\partial S}{\partial x_i} > 0$), and decreasing in others' consumption

[1]It should be noted that consumption is not the only domain where relative preferences have been observed. Recently, Karadja et al. (2017) find that the taste of survey respondents for redistributive policies is associated with their beliefs about their own relative income.

[2]Positional goods are also sometimes referred to as "conspicuous consumption" goods or as "status goods". I use these terms interchangeably.

thereof ($\frac{\partial S}{\partial x_{-i}} < 0$). Consumption of x then imposes a negative externality on others by lowering their status. This results in a general welfare loss and a breakdown of the usual welfare theorems (Dufwenberg et al., 2011).

Various specifications of both preferences and status are found in the literature. The status component is usually modelled in one of two ways. Frank (1985b) initially proposed that the status of consumer i be defined by her *ordinal rank* in the consumption distribution ($f(x)$, $\underline{x} \leq x \leq \bar{x}$) of the positional good:

$$S(x_i) = \int_{\underline{x}}^{x_i} f(x)dx \tag{3.2}$$

An alternative specification of status is based on initial models of relative income (Duesenberry, 1949) and interdependent preferences (Pollak, 1976). Here, status is derived by comparing one's own consumption of good x to a reference level r, which in turn is a function of the consumption of others. Following Akerlof (1997) and Fershtman and Weiss (1998), this reference level is often taken to be the mean consumption level of x:

$$S_i = S(x_i, r = \bar{x}) \ \rightarrow \ U_i = U(x_i, y_i, \bar{x}) \tag{3.3}$$

We shall call this the "*Keeping up with the Joneses*" (KUJ) variety of status-seeking (following Dupor and Liu, 2003). It is typically characterised as a situation where $\frac{\partial \text{MRS}_{y,x}}{\partial \bar{x}} > 0$, i.e. an increase in the reference level $r = \bar{x}$ increases a consumer's desire for the positional good x. Dupor and Liu (2003) investigate the consequences of KUJ preferences, which lead to a consumption externality, for optimal taxation and asset pricing. They model symmetric Nash equilibria involving utility-maximising consumers with homogenous preferences and a simple mean reference level ($\bar{x}$). In Section 3.4, I derive general conditions for the existence and uniqueness of equilibria in societies with status-seeking based on reference levels. I show that a unique equilibrium exists in such an economy under weak assumptions. Since my focus is on income inequality, I allow for asymmetric equilibria and reference levels which give differential weights to consumers. I do not require further assumptions regarding the specific form of preferences or the best-response character of equilibrium.

3.2.2 Inequality and status-seeking consumption: Theory

While growing evidence supports the idea that consumption is motivated by relative considerations, it is less clear how this dynamic relates to the distribution of income. Under which conditions can we posit a systematic relationship between income inequality and the level of status-seeking consumption in a society? As one would expect, this relationship is sensitive to assumptions about consumer preferences and status. The interdependent nature of the various definitions of status-seeking complicates the derivation of general results and closed-form characterisations of behaviour. The bulk of the literature is focused on the implications of status-seeking for optimal taxation (e.g. Aronsson and Johansson-Stenman, 2008; Kanbur and Tuomala, 2013). Fewer contributions explicitly consider the consequences of inequality for the level of status-seeking in an economy.

The few results obtained are based on models where ordinal rank in the consumption distribution of a conspicuous good signals social status (initially proposed by Frank, 1985b). Hopkins and Kornienko (2004) derive comparative statics of Nash equilibrium strategies when status is defined by ordinal rank in a signalling tournament. They show that the relevance of rank-based status competition increases with equality. That is, as the income distribution becomes more compressed, an extra unit of positional consumption hypothetically enables an individual to "overtake" more of her peers in the rank distribution (Samuelson, 2004; Hopkins and Kornienko, 2004). Of course, the zero-sum nature of status makes it so that these gains in rank are not realised. Hopkins and Kornienko (2009) show that more income equality (in the sense of second-order dominance) is likely to increase overall demand for positional goods and to leave a group of poor at the bottom end worse off[3]. Hwang and Lee (2017) provide another perspective on the relationship between status-seeking and inequality. They model status-seeking as a contest between various income groups in society. Again, their model predicts that higher levels of income inequality should result in lower levels of aggregate conspicuous consumption.

An alternative to signalling type models is presented by models of status-seeking where consumers compare their absolute consumption level with that of their peers. It is possible that in such models positional consumption might increase with inequality. Bowles and Park (2005) demonstrate that *upward-looking* status preferences can account for the occurrence of longer working hours in economies with higher income inequality (leisure is usually seen as non-positional, while aggregate consumption is positional). Bowles and Park (2005) use their simple model as motivation for an empirical analysis, but do not characterise equilibria under interdependence of status.

In this chapter, I propose a model of status-seeking where consumption of positional goods is motivated by comparisons to a common reference level, which in turn is shaped by the consumption of all members of society. An advantage of this approach is that it can make use of observed shapes of demand schedules (or Engel curves). This is not the case in the signalling models of status (Hopkins and Kornienko, 2004; Bilancini and Boncinelli, 2012), where conspicuous consumption is modelled as a costly signal without "consumption utility". I thus explicitly take into account rich and poor con-

[3]However, Bilancini and Boncinelli (2012) demonstrate that, in a generalisation of the signalling model where status can have a cardinal element (e.g. the distance between the "rich" and the "poor" matters), opposing forces come into play and can overturn the results of Hopkins and Kornienko (2009).

sumers may have different demands for a good irrespective of its positional character. Throughout, I remain agnostic with regards to the relative importance of consumption preferences and status-seeking in observed consumption patterns.

3.2.3 Inequality and status-seeking consumption: Evidence

Proposing an alternative model of distributional shifts under status-seeking behaviour is motivated by recent empirical observations, some of which contradict the theories discussed above. Frank et al. (2014) provide evidence of so-called "*expenditure cascades*", the phenomenon that middle-income households increase consumption when surrounded by richer peers. Betrand and Morse (2016) show that households at the same income level consume more when they live in US states with higher top income shares. Notably, inequality also distorts consumption towards more visible goods. These findings seem more in line with upward-looking status preferences (Bowles and Park, 2005), but in contradiction with models of status signalling (Hopkins and Kornienko, 2009; Bilancini and Boncinelli, 2012).

The empirical evidence on the link between inequality and status-seeking consumption is, however, far from clear. Charles et al. (2009) find more nuanced results. Using racial categories by US states as relevant reference groups, they find that dispersion of incomes is associated with increases in visible consumption for minorities, but decreases for Whites. Others even find a negative association between inequality and consumption of status goods in the United States (Hwang and Lee, 2017) and India (Roychowdhury, 2017). Throughout this literature, the aggregated nature of this association between income inequality and the level of status-seeking consumption renders causal inference problematic. These analyses also tend to ignore that any link between aggregate demand and the distribution of income may simply be due to consumer preferences—notably the shape of Engel curves for the relevant goods. If status goods are also luxury goods—characterised by convex Engel curves—then we may see higher levels of status consumption in more unequal economies, without this indicating any change in the intensity of status-seeking.

To motivate the theoretical analysis in Sections 3.4 and 3.5, I first explore in Section 3.3 what the Engel curves for status goods may look like. Based on expenditure data for households in the United States, I find concave Engel curves for "visible" goods. I then model status-seeking based on consumption reference levels. In doing so, I hope to provide a tractable alternative to signalling type models (Hopkins and Kornienko, 2004; Bilancini and Boncinelli, 2012), which at the same time can incorporate the shapes of Engel curves and their interaction with status-seeking. Finally, I derive formally the conditions under which a systematic relationship between inequality and demand for status goods may hold.

3.3 Motivating evidence: Visible consumption Engel curves

Any co-movement between income inequality and aggregate consumption of status goods may be because inequality affects the degree of status competition. But it can also result from non-homothetic consumer preferences. Below, I explore the shape of Engel curves for status goods—which describe the average demand for these goods across the income distribution.

To identify status goods, I rely on survey data collected by Heffetz (2011) on the "visibility" of different categories of consumption. Heffetz (2011) divides households' consumption expenditures into 29 categories and assigns to them an index of "visibility" based on the responses of 480 survey participants[4]. Using data from the United States Consumer Expenditure Survey (CEX) provided by the Bureau of Labor Statistics (2009), I link household expenditure to "visibility" scores. Specifically, I use public micro-data from the Interview Survey of the CEX. The data is from the 2009 survey wave, which is the same as used in Chapter 2 above. I follow closely the methodology of Heffetz (2011) building on Harris and Sabelhaus (2000), who assign the ca. 800 UCC expenditure categories from the CEX survey to 109 categories (47 for consumption, 22 for income, and 40 for other). I then assign these 109 expenditure categories to the 29 categories in Heffetz (2011). For the purpose of this chapter, I define visible consumption as expenditures in the 8 categories which constitute the highest quartile of "visibility" as measured by Heffetz (2011). All 29 categories are listed in Appendix Table C.1.

Figure 3.1 depicts the unconditional relationship between annual income of U.S. households (left panel) and visible consumption in 2009. Each point shows average income and visible consumption for one of 20 income bins of equal size. The right panel shows that same relationship for total annual expenditure as an alternative measure of household income[5] (right panel). Assuming that these Engel curves[6] capture

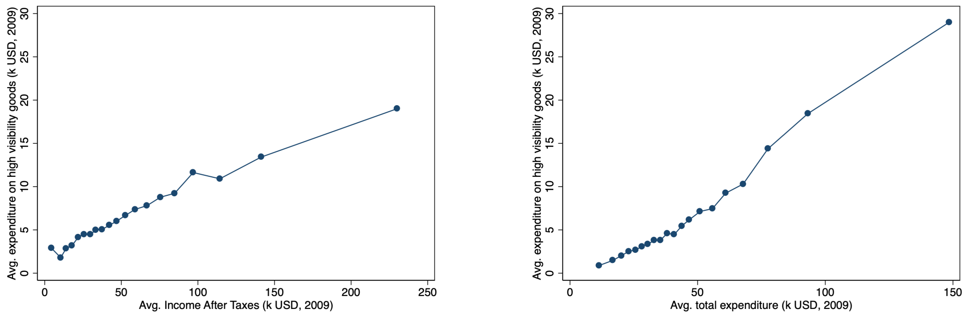
[4]The main question in Heffetz (2011) ranks each consumption category based on the following question: *"Imagine that you meet a new person who lives in a household similar to yours. Imagine that their household is not different from other similar households, except that they like to, and do, spend more than average on [jewelry and watches]. Would you notice this about them, and if so, for how long would you have to have known them, to notice it? Would you notice it almost immediately upon meeting them for the first time, a short while after, a while after, only a long while after, or never?"* Answers are coded from 1 (almost immediately) to 5 (never) and the index is the average response for each category, scaled by $(x-1)/4$ to range between 0 and 1. The survey was carried out by telephone in the United States between May 2004 and January 2005.

[5]Under the assumption of consumption smoothing, annual expenditure may be a better approximation of a consumer's lifetime income.

[6]I call these graphs—plotting absolute income and expenditures—Engel curves. In the demand literature, it is common to call Engel curves the relationship between (log) income and the expenditure share of certain goods. As I have shown in Chapter 2, it is the curvature of absolute Engel curves which translate directly into a relationship between inequality and aggregate demand.

Figure 3.1: Descriptive Engel curves - Visible consumption (2009)

(a) Visible consumption and income **(b)** Visible consumption and expenditure



Notes: Income and expenditure data from the U.S. Consumer Expenditure Survey (CEX), 2009 cross-section. Visible consumption is the sum of annual expenditure (in $) on the 8 (out of 29) consumption categories with the highest level of "visibility" as defined by Heffetz (2011). Averages for each of 20 income bins of equal size. Population weights as provides in the CEX. (a) Horizontal axis: Total annual after-tax income of households. (b) Horizontal axis: Total annual expenditure of households.

the relationship between income and visible consumption, their curvature implies how changes in the distribution of income may influence aggregate visible consumption. Concave Engel curves suggest a negative association between inequality and visible consumption, while convex Engel curves suggest the opposite. From visual inspection the Engel curve in the left panel of Figure 3.1 appears somewhat concave, while the one in the right panel appears somewhat convex. The latter is in line with Heffetz (2011) who finds a positive association when regressing income elasticities of the 29 consumption categories on their "visibility" score.

As discussed in Chapter 2, other household characteristics that covary both with income and consumption may result in Figure 3.1 being biased. To obtain an estimate of the relationship between income and visible consumption—conditional on other household characteristics remaining the same—I run a linear regression of the form:

$$y_i = \beta_1 m_i + \beta_2 m_i^2 + \mathbf{x_i}'\delta + \varepsilon_i \tag{3.4}$$

Here, y_i is visible consumption expenditure of household i, m_i is that household's income, and the vector $\mathbf{x_i}$ contains a range of relevant household characteristics. As in Chapter 2, this approach accounts for partial linear associations between income, visible consumption, and other household characteristics. These regression-based, parametric Engel curves provide suggestive evidence as to how households may adjust their visible consumption when their income level changes, while holding constant their other characteristics in $\mathbf{x_i}$. Table 3.1 shows results from these regressions in four variations. In the first two columns, annual household income after taxes (in k USD) is used as income measure m_i. Column 1 shows the coefficient estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ without controlling for household characteristics. Column 2 shows coefficient estimates when $\mathbf{x_i}$ includes controls for family size, family size (squared), age of HH head, age (squared), marital status, education, race, region. Using the coefficient estimates from Column 2, an additional 1000 USD of annual after tax income is associated with 83 USD more in visible consumption for a household with an income of 50K USD, while this number drops to about 70 USD when the household has an income of 200K USD. Columns 3 and 4 show equivalent results when using total annual expenditure as a measure of income instead.

The results across specifications suggest that Engel curves for visible consumption, after controlling for household characteristics, are concave (given $\hat{\beta}_2 < 0$). Concavity of Engel curves usually goes hand in hand with income elasticities below 1. Put differently, visible consumption behaves like a necessity—low income consumers spend a higher share of their incomes on visible consumption. Concave absolute Engel curves also suggest that progressive income redistribution may raise aggregate visible consumption as long as households follow the pattern prescribed by equation (3.4). As shown in Chapter 2, it is possible to quantify the predicted increase in visible consumption when transferring 1000 USD from the richer to the poorer among two households randomly drawn from the income distribution. Results in Table 3.1 suggest that this would raise the content of portion of those 1000 USD used for visible consumption by 8-12%[7].

In sum, observed household expenditure patterns suggest a negative association between income inequality and aggregate consumption of status goods. This analysis of household expenditure patterns does thus not support the hypothesis that inequality leads to higher demand for status goods. But since status-seeking is by definition relative to the observed consumption of peers, it results in consumer preferences being endogenous. More precisely, changes in the consumption choices by i and j may well have knock-on effects on other consumers and each other. Whether these knock-on effects of status-seeking may overturn the negative association between inequality and visible consumption implied by concave Engel curves is the question asked below.

[7] As shown in Chapter 2, when choosing at random two households from the income distribution $F(m)$, and re-distributing a small amount of income from the richer household j to the poorer one i, the expected change in aggregate y is $E_{ij}(\frac{\partial y_i}{\partial m_i} - \frac{\partial y_j}{\partial m_j}|m_j > m_i) = -2\beta_2\Psi(F(m))$ where $\Psi(F(m))$ is Gini's Mean Difference, $\Psi(F(m)) = \int\int |y-z|dF(y)dF(z)$.

Table 3.1: Quadratic Engel curves - Visible consumption (2009)

	Income		Expenditure	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Income (k USD, 2009)	105.524***	87.139***		
	(6.9067)	(7.8015)		
Income squared	-0.129***	-0.084**		
	(0.0327)	(0.0339)		
Expenditure (k USD, 2009)			247.526***	269.034***
			(9.8530)	(12.4705)
Expenditure squared			-0.197***	-0.219***
			(0.0114)	(0.0100)
Observations	4,407	4,378	4,407	4,378
R-squared	0.20	0.21	0.54	0.56
Household characteristics	NO	YES	NO	YES
Implied distributional comparative statics				
Avg. visible cons. (per 1000 USD)	116.1	116.1	147.5	147.5
$-2\hat{\beta}_2\Psi(F(m))$	14.27	9.25	12.76	14.24
Marginal change from redistribution	**12.3%**	**8.0%**	**8.7%**	**10.0%**

Notes: Estimates from OLS regression of equation (3.4). Each time the dependent variable visible consumption, the sum of annual expenditure (in $) on the 8 (out of 29) consumption categories with the highest level of "visibility" as defined by Heffetz (2011). All other variables from the U.S. Consumer Expenditure Survey (CEX), 2009 cross-section. Household characteristics include family size, family size squared, age of household head, age of household head squared, a binary marriage indicator, binary indicators for race ("Black", "Native American", "Asian/Pacific", "Pacific Islander", "Multi-race"), indicators of educational attainment ("below high school", "some college/vocational", "college degree or higher"), and indicators of region ("Midwest", "South", "West"). Population weights as provides in the CEX. Households with negative reported after-tax income and income above $400K excluded. "$-2\hat{\beta}\Psi(F(m))$" is the predicted increase (USD) in visible consumption from progressively redistributing 1000 USD between two households drawn at random from the income distribution. Heteroskedasticity-robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.4 Model: Status-seeking with a reference level

In this section I outline a model of status-seeking based on a common reference level, which influences individual consumers' demand for a positional good. In equilibrium, the demand of individual consumers must then re-produce the reference level it is based on. I show that the equilibrium in such an economy exists and is unique under plausible assumptions. I also discuss how it can be the outcome of an underlying process of repeated pairwise comparisons between consumers.

Let us consider the demand of consumer i for a positional good, $x_i \in X \subset \mathbb{R}_+$. Let us assume that consumption is constrained by personal income $m_i \in M \subset \mathbb{R}_+$ and influenced by a reference level $r \in R \subset \mathbb{R}_+$ common to all consumers. We assume that consumers have homogeneous preferences, which can be represented by the demand function $x : M \times R \to X$. We thus abstract from changes in prices (as well as other goods) and individual demand is solely determined by individual income and the common reference level. The demand function of consumer i for good x is:

$$x_i = x(m_i, r) \tag{3.5}$$

Let us further assume that $x(.)$ is continuously differentiable in m and r, that x is a normal good ($\frac{\partial x(.)}{\partial m} > 0$) and that consumers seek status ($0 \leq \frac{\partial x(.)}{\partial r} < 1$). Finally, assume that the reference level is a weighted mean of consumption by the N consumers:

$$r := \sum_{i=1}^{N} \alpha_i x_i \quad \text{s.t. } \alpha_i \geq 0 \; \forall i = 1, ..., N \text{ and } \sum_{i=1}^{N} \alpha_i = 1 \tag{3.6}$$

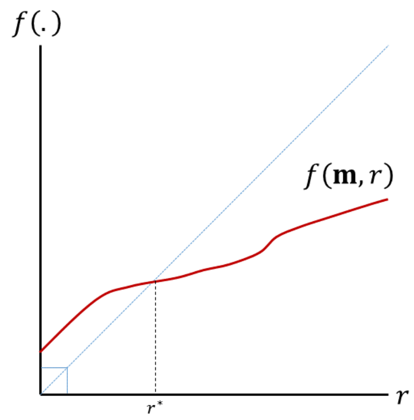
I call α_i the "status-relevance" of consumer i, as it describes the relative weight[8] of i in the common reference level r. The formation of the reference level depends on the vector of incomes $\mathbf{m}$ and the reference level. This is summarised in the function $f(\mathbf{m}, r) = f(x(m_1, r), ..., x(m_N, r)) = \sum_{i=1}^{N} \alpha_i x(m_i, r)$. These assumptions are rather weak and compatible with a range of applications. It is straightforward to show that there exists a unique reference-point equilibrium in such an economy.

Proposition 4 *Assume that demand $x(.)$ is continuously differentiable in income m and a reference level r, with $\frac{\partial x(.)}{\partial m} > 0$ and $0 \leq \frac{\partial x(.)}{\partial r} < 1$. Further assume that $r := \sum_{i=1}^{N} \alpha_i x_i$ with $\alpha_i \geq 0 \; \forall i = 1, ..., N$ and $\sum_{i=1}^{N} \alpha_i = 1$. Then, for any income distribution $\mathbf{m} \in M^N \subset \mathbb{R}_+^N$, there exists a unique, stable reference-point equilibrium where $r^* = f(\mathbf{m}, r^*) = \sum_{i=1}^{N} \alpha_i x(m_i, r^*)$.*

Proof. See Appendix C.3.1. ■

[8] Status-relevance may be linked to behavioural traits (e.g. extroversion or expressiveness) or social standing (e.g. age, gender, or ethnicity). Here, I consider a set of such weights that is exogenously given and maintain that all consumers have the same reference level r.

Figure 3.2: Illustration of equilibrium condition for reference level



Notes: Illustration of the reference-point formation function $f(.)$ for a given income distribution $\mathbf{m} \in M^N \subset \mathbb{R}^N_+$. Equilibrium is where the reference level that consumers react to (horizontal axis) re-creates that reference level (vertical axis).

In essence, equilibrium is attained when consumption behaviour, as shaped by the reference level r, reproduces said reference level[9]. This situation is depicted in Figure 3.2. For an arbitrary given distribution of incomes ($\mathbf{m} \in M^N \subset \mathbb{R}^N_+$), the function $f(.)$ describes how a given reference level (horizontal axis) translates—via the individual consumption choices by all individual consumers and their weight in the reference level—into a new reference level (vertical axis). Equilibrium is where $f(.)$ crosses the 45^o-line.

While I frame this discussion as the outcome of status-seeking consumption, the same behaviour can result from other types of social feedback mechanisms, for example when consumption goods are subject to positive network externalities as proposed by Katz and Shapiro (1985)[10]. A common example of network externalities is the demand for electric vehicles which may increase with the number of charging stations and thus the number of vehicles on the road. Such network externalities might then also be captured by the model proposed here.

[9] In modelling status-seeking as a fixed-point between consumer choice and reference levels, I do not intend to suggest that the outcome necessarily represents a Nash equilibrium, resulting from strategic introspection and mutually consistent, best-response strategies. As the equilibrium is stable, it may simply be a point of gravity for a process of repeated adaptation of consumption patterns.

[10] To be precise, Katz and Shapiro (1985) define network externalities as a situation where the utility a consumer derives from a good is increasing in the consumption thereof by her peers. In the KUJ setting, it is the marginal utility of that good which increases with peer consumption, while the utility level is likely to fall. In this chapter, I abstract from the notion of utility and focus on demand directly, which is plausible to increase in many variations of either situation.

3.4.1 Example: A reference level from pairwise interaction

Consumers may indeed have a reference level in mind when making decisions. But equivalent behaviour can also result from more spontaneous status-seeking. For example, behaviour equivalent to following a reference level can be the long run outcome of repeated pairwise comparisons. Depending on the degree of loss aversion—the distaste for being worse off relative to being better off—pairwise comparisons can result in behaviour equivalent to that in either of two common models of consumption reference levels. To show this, I re-appropriate a simple model of reference-dependence under uncertainty (Bowman et al., 1999; Koszegi and Rabin, 2006) who consider individual utility of a consumer from monetary payoff c and reference level r:

$$u(c|r) \equiv m(c) + n(c|r) = m(c) + \mu(m(c) - m(r)) \tag{3.7}$$

I consider comparisons to peers drawn randomly from the income distribution, yielding a stochastic reference level r distributed according to $G(r)$. I focus on the special case of "constant sensitivity" with both $m(.)$ and $\mu(.)$ linear. Individual utility is then:

$$u(c|G) \equiv \int [c + \mu \cdot (c-r) \cdot \mathbf{1}|_{c>=r} + \mu \cdot (c-r) \cdot \lambda|_{c<r}] dG(r) \tag{3.8}$$

I re-interpret this model to fit pairwise comparisons between consumers. Let x_i be the consumption of a positional good and x_j the consumption level of a peer. The average (or expected) experienced consumption of consumer i, $\hat{x}(x_i|G(x))$, is then:

$$\begin{aligned}
\hat{x}(x_i|G(x)) &= \int_{x_{lo}}^{x_{hi}} [x_i + \mu(x_i - x) \cdot \mathbf{1}|_{x_i>=x} + \mu(x_i - x) \cdot \lambda|_{x_i<x}] dG(x) \\
&= x_i + \int_{x_{lo}}^{x_i} [\mu(x_i - x)] dG(x) + \int_{x_i}^{x_{hi}} [\mu\lambda(x_i - x)] dG(x) \\
&= x_i + \mu(x_i - \bar{x}) + \mu(\lambda - 1)(x_i - \bar{x}_i^{up})
\end{aligned} \tag{3.9}$$

Here, $\bar{x}_i^{up}$ is mean consumption above x_i. I normalise $\mu = \frac{\eta}{\lambda}$ and assess the limiting cases of no loss aversion (Case A: $\lambda = 1$) and extreme loss aversion (Case B: $\lambda \to \infty$):

$$\hat{x}(x_i|G(x)) = x_i + \eta\frac{1}{\lambda}(x_i - \bar{x}) + \eta\frac{\lambda - 1}{\lambda}(x_i - \bar{x}_i^{up}) \tag{3.10}$$

$$\text{Case A:} \quad \hat{x}(x_i|G(x)) = x_i + \eta(x_i - \bar{x}) = (1+\eta)x_i - \bar{x} \tag{3.11}$$

$$\text{Case B:} \quad \lim_{\lambda\to\infty}\hat{x}(x_i|G(x)) = x_i + \eta(x_i - \bar{x}_i^{up}) = (1+\eta)x_i - \bar{x}_i^{up} \tag{3.12}$$

Pairwise comparison nests two common models of status-seeking. Without loss aversion, (A) agents behave as if comparing themselves to mean consumption ($\bar{x}$). That is *"KUJ status-seeking"*. Under extreme loss aversion, (B) agents behave as if comparing themselves to those better off ($\bar{x}_i^{\text{up}}$). That is *"trickle-down consumption"*.

3.5 Distributional comparative statics

Can we posit a systematic relationship between income inequality and status-seeking? In this section I derive distributional comparative statics under the reference-point equilibrium described in Section 3.4. The function of interest is (mean) aggregate positional consumption given the reference-level is in equilibrium:

$$\bar{x} = \bar{x}(\mathbf{m}, r) = \frac{1}{N}\sum_{i=1}^{N} x(m_i, r) \text{ s.t. } r = f(\mathbf{m}, r) = \sum_{i=1}^{N} \alpha_i x(m_i, r) \tag{3.13}$$

Throughout, I consider a transition from income distribution A to income distribution B, represented respectively by the vectors $\mathbf{m_A}, \mathbf{m_B} \in \mathbb{R}_+^N$ with the same total income ($\sum_{i=1}^N m_{A,i} = \sum_{i=1}^N m_{B,i}$). Without loss of generality, we can assume that B is more equal than A, in the sense that $\mathbf{m_B}$ can be arrived at through a finite number of Pigou-Dalton transfers[11] (from a consumer with higher income to one with lower income) starting from (a permutation of) $\mathbf{m_A}$. This is equivalent to $\mathbf{m_A}$ *majorising* $\mathbf{m_B}$ ($\mathbf{m_A} \succ_m \mathbf{m_B}$). Going from A to B would be considered a decrease in inequality by all common discrete inequality measures satisfying the Pigou-Dalton principle of transfers (see e.g. Marshall and Olkin, 1979; Cowell, 2011). These inequality measures are Schur-convex.

Definition 1 (Majorisation) *Let $\mathbf{x}, \mathbf{y} \in \mathbb{R}_+^N$ and let $x_{(.)} = (x_{(1)}, ..., x_{(N)})^T$ and $y_{(.)} = (y_{(1)}, ..., y_{(N)})^T$ be their ordered versions ($x_{(1)} \leq x_{(2)} \leq x_{(3)}...$). We say that $\mathbf{x}$ majorises $\mathbf{y}$, $\mathbf{x} \succ_m \mathbf{y}$ iff $\sum_{i=1}^N x_i = \sum_{i=1}^N y_i$ and $\sum_{i=1}^k x_{(i)} \leq \sum_{i=1}^k y_{(i)}$ for any $k = 1, 2, ..., N$.*

Definition 2 (Schur-convexity) *A function $f : M^N \to \mathbb{R}$ is Schur-convex when, for all $\mathbf{x}, \mathbf{y} \in M^N \subset \mathbb{R}^N$, $\mathbf{x} \succ_m \mathbf{y} \;\to\; f(\mathbf{x}) \geq f(\mathbf{y})$. It is Schur-concave when $-f$ is Schur-convex.*

As shown in Section 3.4, there is a unique reference-point equilibrium under each income distribution, respectively defined by $r_A = f(\mathbf{m_A}, r_A)$ and $r_B = f(\mathbf{m_B}, r_B)$. Aggregate (mean) positional consumption in those equilibria is $\bar{x}(\mathbf{m_A}, r_A)$ and $\bar{x}(\mathbf{m_B}, r_B)$ respectively. I list in Table 3.2 the notation for the main elements of the analysis.

[11] Sometimes these transfers are referred to as (elementary) T-transforms.

Table 3.2: Main elements and notation

Notation	Concept
$x(m_i, r)$	Demand of a consumer with income m_i and reference level r
$\mathbf{m_A}, \mathbf{m_B} \in \mathbb{R}^N_+$	Income distributions represented as N-dimensional vectors
$r_A = f(\mathbf{m_A}, r_A)$	Equilibrium reference level under income distribution A
$\bar{x}(\mathbf{m_A}, r_A)$	Aggregate (mean) positional consumption under income distribution A and reference level r_A (in equilibrium)
$\bar{x}(\mathbf{m_B}, r_A)$	Aggregate (mean) positional consumption under income distribution B and reference level r_A (out of equilibrium)

Notes: List of key terms and notation discussed in the text.

The key questions I would like to answer in this section are as follows:

1. Under what conditions is positional consumption unambiguously increasing (decreasing) in income inequality, i.e. $\bar{x}(\mathbf{m_A}, r_A) > (<) \bar{x}(\mathbf{m_B}, r_B)$ when $\mathbf{m_A} \succ_m \mathbf{m_B}$?
2. Under what conditions can we predict the direction of change based on the shape of (static) Engel curves under the old equilibrium, in the sense that $\text{sign}[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] = \text{sign}[\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)]$?

The first question is concerned with the conditions necessary in theory for a systematic relationship between inequality and positional consumption. It is motivated by the mixed findings in the previous literature discussed in Section 3.2. Formally, we are looking for conditions under which aggregate consumption $\bar{x}(\mathbf{m}|r = f(\mathbf{m}, r))$ (in equilibrium) is either Schur-convex or Schur-concave. I have shown in Section 3.3 that household expenditure patterns in the United Sates suggest a negative association due to concave Engel curves for visible consumption. However, the observed Engel curves are not sufficient to predict the change in aggregate consumption when the behaviour of individual consumers is influenced by that of other consumers. Observed Engel curves are the product of the original reference level. Any shift in income may not only move consumers along the Engel curve, but may also—by changing the reference level—affect the shape of the Engel curve itself.

The second question is concerned with the conditions necessary to predict the direction of that relationship based on observable outcomes. Let us consider the information available to an empirical researcher who has estimated the shape of Engel curves for visible consumption as I have in Table 3.1. These Engel curves describe demand at a given reference level, $x(m, r_A)$, over different values of income m. But we are unlikely to observe the reference level r_A or how changes in it affect consumption. We thus have no information about the possible shape of $x(m,r_B)$ under the new equilibrium and, consequently, $\bar{x}(\mathbf{m_B},r_B)$. We can only predict $\bar{x}(\mathbf{m_B},r_A)$ based on the shape of observed Engel curves. This allows for prediction of $[\bar{x}(\mathbf{m_B},r_A)-\bar{x}(\mathbf{m_A},r_A)]$ even when r_A is unobserved (by simply shifting mass in the income distribution across static Engel curve). A researcher can then predict the direction of the change in aggregate consumption levels if $\text{sign}[\bar{x}(\mathbf{m_B},r_B)-\bar{x}(\mathbf{m_A},r_A)] = \text{sign}[\bar{x}(\mathbf{m_B},r_A)-\bar{x}(\mathbf{m_A},r_A)]$. In words, we are looking for conditions ensuring that the direction of change in aggregate positional consumption from an old to a new equilibrium characterised by reference level r_B, which we cannot observe or predict, is the same as that predicted if the reference level were to remain r_A while the distribution of income changes from $\mathbf{m_A}$ to $\mathbf{m_B}$.

3.5.1 Comparative statics with simple mean reference level

In a range of applications, the reference level is taken to be the simple mean of consumption $r=\bar{x}$ (e.g. Akerlof, 1997; Fershtman and Weiss, 1998; Bowles and Park, 2005). This is the special case where $\alpha_i = \frac{1}{N}\ \forall\ i = 1,...,N$ and is commonly referred to as "Keeping up with the Joneses" (KUJ) preferences (Dupor and Liu, 2003). A specific example is given in Appendix C.2. In this case the direction of change implied under the current reference level r_A is sufficient to predict the direction of change when moving from income distribution A to B. This result is summarised in Lemma 1.

Lemma 1 (Simple mean consumption reference level) *With simple mean consumption as the reference level $r := \sum_{i=1}^{N}\frac{1}{N}x_i$, a shift to a new income distribution moves aggregate (mean) positional consumption in the same direction as suggested by demand functions under the previous equilibrium. More generally, for any $\mathbf{m_A},\mathbf{m_B}\in M^N\subset\mathbb{R}^N_+$, it holds that* $\text{sign}[\bar{x}(\mathbf{m_B},r_B)-\bar{x}(\mathbf{m_A},r_A)] = \text{sign}[\bar{x}(\mathbf{m_B},r_A)-\bar{x}(\mathbf{m_A},r_A)]$.
Proof. See Appendix C.3.2. ■

A single transfer between two consumers will always move aggregate (mean) positional consumption in the same direction as would be expected under the old equilibrium (i.e. assuming that incomes change, but the reference level r_A does not). This is especially relevant to empirical applications which rely on estimates of Engel curves depicting average consumption of x at different points of the income distribution for a given reference point. Under the assumption that households have homogeneous preferences—when their income changes they move along the Engel curves—the relationship between aggregate positional consumption and the distribution of income relies entirely on the shape of the (static) Engel curves.

Proposition 5 (Convex Engel curves yield Schur-convex aggregate demand) *With simple mean consumption as the reference level $r := \sum_{i=1}^{N} \frac{1}{N} x_i$, aggregate (mean) positional consumption will be unambiguously higher (lower) under any income distribution B which is "more equal" than distribution A iff the (static) Engel curves are strictly concave (convex). More precisely, $\bar{x}(\mathbf{m_B}, r_B) > (<) \bar{x}(\mathbf{m_A}, r_A)$ for any $\mathbf{m_A}, \mathbf{m_B} \in M^N \subset \mathbb{R}_+^N$ with $\mathbf{m_A} \succ_m \mathbf{m_B}$ (without $\mathbf{m_B} \succ_m \mathbf{m_A}$) iff $\frac{\partial^2 x(m,r)}{\partial m^2} < (>) 0 \; \forall m, r \in M \subset \mathbb{R}_+$.*

Proof. See Appendix C.3.3. ■

As inequality measures are generally Schur-convex, a systematic positive (or negative) association between inequality and positional consumption requires that aggregate positional consumption $\bar{x}(\mathbf{m}|r = f(\mathbf{m}, r))$ (in equilibrium) is Schur-convex (or Schur-concave). Proposition 5 shows that, if the reference level is the simple mean of positional consumption, then $\bar{x}(\mathbf{m}|r = f(\mathbf{m}, r))$ will be Schur-concave if Engel curves $x(m, r)$ are concave, as I found them to be in Section 3.3. Put differently, status dynamics cannot overturn the comparative statics implied by the shape of Engel curves.

Finally, when consumers are strictly status-seeking for at least some of the income levels concerned, the social feedback mechanism amplifies the change in aggregate consumption in the same direction as implied under the old equilibrium.

Proposition 6 (Status-seeking acts as a multiplier effect) *When there is nonzero status-seeking, i.e. when $\frac{\partial f(\mathbf{m}, r)}{\partial r} > 0$, then status-seeking with a simple mean reference level $r := \sum_{i=1}^{N} \frac{1}{N} x_i$ amplifies the comparative statics suggested by static Engel curves in the same direction, i.e. $|\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)| > |\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)|$ whenever $\bar{x}(\mathbf{m_B}, r_A) \neq \bar{x}(\mathbf{m_A}, r_A)$.*

Proof. See Appendix C.3.4. ■

The above findings translate into the following insights for empirical settings: (a) observed demand (static Engel curves) can be useful in predicting distributional comparative statics despite status-seeking under the assumptions underlying Lemma 1 and Proposition 5; (b) whether or not aggregate consumption of a good moves in the direction predicted based on static Engel curves when the income distribution changes exogenously, presents a first test of those assumptions; and (c) based on Proposition 6, when two goods have identical static Engel curves, the more "status-relevant" of the two will respond more strongly to an exogenous change in income distribution. This might be testable using proxies of "status-relevance", such as "visibility" of consumption goods (Charles et al., 2009; Heffetz, 2011). Given the evidence from household expenditure patterns in Section 3.3, we would then expect that income inequality is associated with lower aggregate consumption of status goods when the reference level is the simple mean of positional consumption.

3.5.2 Comparative statics with weighted mean reference level

The above analysis has shown that the observed Engel curves are useful for predicting the change in aggregate positional consumption from redistributing incomes as long as the reference level is the simple mean of consumption. However, not all consumers may have an equal influence on the common reference level for consumption. For example, we may imagine that certain individual consumers are more "visible" or "relevant" in the formation of the consumption reference level due to their prominence, location, behaviour, or other personal traits. I now explicitly allow for such differences in "status-relevance" ($\exists(i,j)$ s.t. $\alpha_i \neq \alpha_j$). The reference formation function $f(\mathbf{m},r)$ is then no longer symmetrical and neither is aggregate positional consumption in equilibrium. To see this, consider a single Pigou-Dalton transfer of income Δ from a higher income consumer j to a lower income consumer i ($m_i < m_j$ and usually $\Delta < \frac{m_j - m_i}{2}$) starting from an equilibrium reference level r_A and leading to equilibrium reference level r_B. In this case status-seeking can potentially overturn comparative statics implied by static Engel curves.

Proposition 7 (Reversal of distributional comparative statics) *Starting from an initial income distribution* $\mathbf{m}_A$ *with equilibrium reference level* r_A*, an incremental transfer* $\Delta \to 0_+$ *from* j *to* i *will move aggregate (mean) positional consumption in the opposite direction as implied by static Engel curves in two cases. More specifically, a reversal of implied comparative statics will occur for a small enough transfer* Δ *when either:*

Case A:

$$0 < \left(\frac{\partial x(m_i,r_A)}{\partial m} - \frac{\partial x(m_j,r_A)}{\partial m}\right) < -\Psi(\mathbf{m},r_A)\left(\alpha_i \frac{\partial x(m_i,r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j,r_A)}{\partial m}\right)$$

Case B:

$$0 > \left(\frac{\partial x(m_i,r_A)}{\partial m} - \frac{\partial x(m_j,r_A)}{\partial m}\right) > -\Psi(\mathbf{m},r_A)\left(\alpha_i \frac{\partial x(m_i,r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j,r_A)}{\partial m}\right)$$

where $\Psi(\mathbf{m},r_A) = \left(\sum_{k=1}^{N} \frac{\partial x(m_k,r_A)}{\partial r}\right) \frac{1}{1-\frac{\partial f(\mathbf{m},r_A)}{\partial r}} = \left(\sum_{k=1}^{N} \frac{\partial x(m_k,r_A)}{\partial r}\right) \frac{1}{1-\sum_{l=1}^{N} \alpha_l \frac{\partial x(m_l,r_A)}{\partial r}}.$

Proof. See Appendix C.3.5. ■

Proposition 7 makes clear that we now have to consider two types of effects on aggregate (mean) positional consumption $\bar{x}$ from any income transfer Δ: (i) the change in consumption of i and j in response to their changed incomes, i.e. the gradient of the Engel curve (middle portion of either equation), and (ii) the corresponding change in the reference level which results in further adjustments by all consumers until the new equilibrium reference level is reached (final portion of either equation).

If both of these dynamics act in the same direction, that will be the direction in which the new equilibrium aggregate (mean) positional consumption $\bar{x}(\mathbf{m_B}, r_B)$ lies. This is trivially the case when the reference level is the simple mean, i.e. $\alpha_i = \alpha_j = \frac{1}{N}$, as Lemma 1 has shown. However, if these two changes go in opposite directions, it is possible for the change in reference level (and the cycle of reactions to it) to outweigh the immediate change in consumption by i and j.

Proposition 7 states exactly the two cases when, for a small enough transfer, the immediate change in consumption by i and j in response to the income transfer is outweighed, in the opposite direction, by the immediate change in reference level multiplied by the "status feedback" multiplier $\Psi(\mathbf{m}, r_A)$. Both these cases become less likely when:

- $|\frac{dx(m_i,r_A)}{dm} - \frac{dx(m_j,r_A)}{dm}|$ is large (i.e. more curved Engel curves)
- $|\alpha_i - \alpha_j|$ is small (i.e. more equal consumers in terms of status-relevance)
- Ψ is small (i.e. lower status-seeking generally, $\sum_{k=1}^{N} \frac{\partial x(m_k,r_A)}{\partial r}$, and lower correlation of individual status-sensitivity $\frac{\partial x(m_k,r_A)}{\partial r}$ and status-relevance α_k.)

I initially set out to define conditions under which we can be certain of the relationship between income inequality and aggregate positional consumption. Formally, we are looking for conditions under which aggregate consumption (in equilibrium) $\bar{x}(\mathbf{m}, r = f(\mathbf{m}, r))$ is either Schur-convex or Schur-concave. A consequence of Proposition 7 is that, when status-relevance weights α_i are person-specific and not all equal, such conditions do not exist. This negative result in formalised in Corollary 1.

Corollary 1 ***(Person-specific weights)*** *When status-relevance weights are person-specific ($\{\alpha_i\}_{i=1,\dots,N}$) and not all the same ($\exists(i, j)$ s.t. $\alpha_i \neq \alpha_j$), then for any $\mathbf{m_A} \in \mathbb{R}_+^N$ that is not perfectly equal ($m_i = m_j \; \forall i, j = 1, \dots, N$), there exist $\mathbf{m_B}, \mathbf{m_C} \in \mathbb{R}_+^N$ with $\mathbf{m_A} \succ_m \mathbf{m_B}$ and $\mathbf{m_C} \succ_m \mathbf{m_A}$, such that either (i) $\bar{x}(\mathbf{m}_B, r_B) > \bar{x}(\mathbf{m}_A, r_A)$ and $\bar{x}(\mathbf{m}_C, r_C) > \bar{x}(\mathbf{m}_A, r_A)$ or (ii) $\bar{x}(\mathbf{m}_B, r_B) < \bar{x}(\mathbf{m}_A, r_A)$ and $\bar{x}(\mathbf{m}_C, r_C) < \bar{x}(\mathbf{m}_A, r_A)$. This is true even if the (static) Engel curves are strictly concave or convex.*

Proof. See Appendix C.3.6. ■

Corollary 1 suggests that there cannot be a systematic relationship between income inequality and aggregate positional consumption if status-relevance weights $\{\alpha_i\}_{i=1,\dots,N}$ are person-specific. For a small enough transfer between two individuals, the direction of change of aggregate positional consumption can be entirely determined by the difference in α_i and α_j. There will be a permutation of the same income distribution over the same individuals, which inverts the comparative statics for such a transfer. Put differently, it matters *who* is at what position in the income distribution. This is a direct consequence of *person-specific* status-relevance weights resulting in aggregate consumption not being a symmetric function over $\mathbf{m}$. For $\bar{x}(\mathbf{m}, r = f(\mathbf{m}, r))$ to be either Schur-convex or Schur-concave, it has to be symmetric, i.e. that the status-relevance weights $\{\alpha_i\}_{i=1,...,N}$ are fully determined by income. For example, they could be attached to the position in the income distribution rather than to the specific person. This insight in summarised in Corollary 2.

Corollary 2 ***(Position-specific weights)*** *If status-relevance weights $\alpha_{(i)}$ are position-specific and not all the same, $\bar{x}(\mathbf{m}, r = h(\mathbf{m}, r))$ will be Schur-convex (Schur-concave) iff static Engel curves are convex (concave), i.e. $\frac{\partial^2 x(m,r)}{\partial m^2} \geq (\leq) 0 \ \forall (m,r) \in \mathbb{R}^+$, and weights are non-decreasing (non-increasing) in income, $\alpha_{(i)} \leq \alpha_{(i+1)} \ \forall i = 1, ..., N-1$.*
Proof. Direct consequence of Proposition 7. ■

Corollary 2 states that it may be possible for a systematic relationship between inequality and positional consumption to exist if status-relevance weights are purely determined by income. Switching the income of two consumers will also switch their weights in the reference level. In this case aggregate consumption is symmetric and thus could be either Schur-convex or Schur-concave.

The discussion of this section has shown how status-seeking alters the comparative statics of aggregate consumption with respect to the income distribution. In the absence of status-seeking, we can posit a systematic relationship between aggregate consumption of a good x and income inequality as long as Engel curves for that good are either strictly concave or convex. As shown in Lemma 1, this remains true when status-seeking is defined by a common reference level which is the simple mean of consumption $r = \bar{x}$. However, when consumers differ in terms of "status-relevance" ($\exists (i, j)$ s.t. $\alpha_i \neq \alpha_j$), the comparative statics implied by Engel curves can potentially be overturned as shown in Proposition 7. As shown in Corollaries 1 and 2, a systematic relationship between inequality and positional consumption can only hold if "status-relevance" is monotonic in income. An extreme version of this is "trickle-down consumption" with purely upward-looking status-seeking.

Distributional Comparative Statics under "Trickle-down": Status-seeking that is purely upward-looking leads to a process of "trickle-down consumption". Each consumer i the sets of peers affecting her actions and those affected by her do not overlap. The economy is no longer adequately described by an equilibrium. Rather, any change in incomes leads to iterative adjustments of consumption from the top down. The comparative statics with respect to the income inequality depend on the chosen formulation of consumer preferences and the shape of the income distribution along its entirety. Generally speaking, in such an economy there is a tendency for higher top income shares to have especially large impact on aggregate positional consumption. I present a specific example for this in Appendix C.2.

3.6 Discussion: Status-seeking and pollution

How status-seeking influences consumer behaviour may have important implications for environmental policy. As discussed in Chapter 2, the concavity of Environmental Engel curves (EECs) suggests that progressive income redistribution may raise aggregate greenhouse emissions embedded in consumption. Underlying this dilemma is the assumption that consumers receiving income transfers will move along the EECs. However, relative consumption effects might result in the shape of Engel curves changing as income is redistributed. It is then no longer clear that the "equity-pollution dilemma" will hold. Two questions arise when trying to assess the implications of status-seeking for the "equity-pollution dilemma": First, is income inequality systematically related to more (or less) demand for status goods? Second, are status goods systematically more (or less) emissions intensive than other types of consumption?

The first question is treated in Sections 3.3, 3.4 and 3.5. I discuss above the conditions under which income inequality may be systematically related to the aggregate demand for status goods. In a model of status-seeking based on a common reference level, these conditions rely both on the shape of Engel curves for status goods and the weight of consumers at different income levels in shaping the reference level. With a simple mean reference level, the direction of change is fully determined by the former. Looking at the consumption of U.S. households, I find that Engel curves for "visible" goods are concave, which by itself suggests a negative association between inequality and positional consumption. However, I also show that this association can be overturned if status-relevance is increasing with income to a sufficient degree. This is certainly possible, but I am not aware of any evidence showing this.

The second question, concerning the relationship between status-seeking and the environmental burden of consumption, has been little studied to date[12]. At the aggregate level, we may argue that all consumption is subject to relative consumption effects—as consumption is more conspicuous than either savings (Moav and Neeman, 2012) or leisure (Bowles and Park, 2005; Arrow and Dasgupta, 2009). Insofar as aggregate consumption is more polluting than savings or leisure, we may then expect status-seeking to be detrimental to environmental outcomes[13].

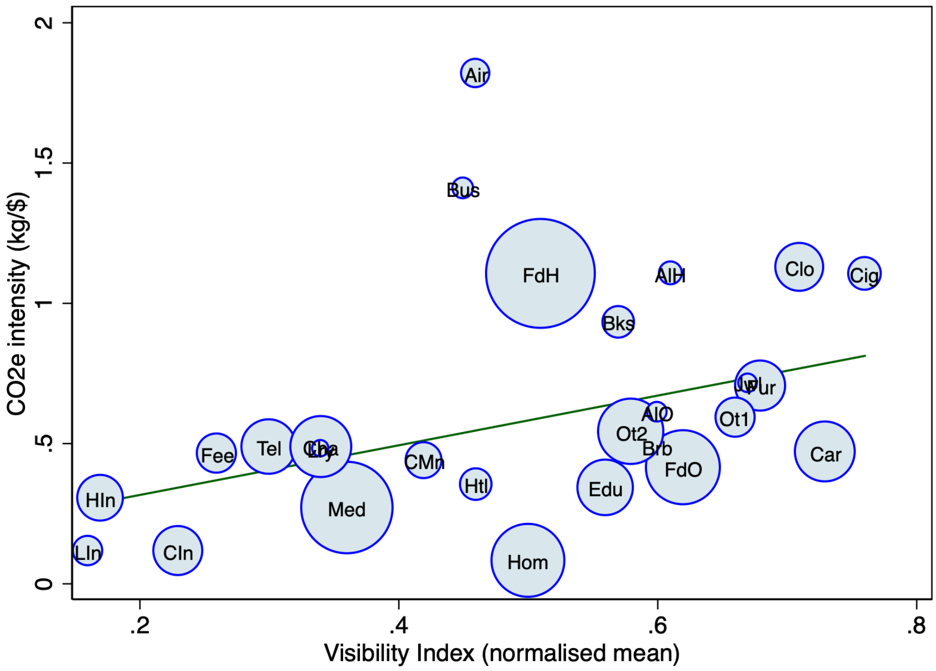
At a disaggregated level it is unclear if status goods are more or less polluting. I provide suggestive evidence on this in Figure 3.3, which contrasts the greenhouse gas content (CO_2e) of consumption categories with their degree of "visibility"[14]. The

[12]Contributions linking relative consumption to pollution have so far focused on implications for Pigouvian taxes (e.g. Welsch, 2009; Dasgupta et al., 2016; Ulph and Ulph, 2019) and the discounting of climate damages (Johansson-Stenman and Sterner, 2015).

[13]Arrow and Dasgupta (2009) point out that today's savings may turn into tomorrow's consumption, generating future status and pollution.

[14]The greenhouse gas content of consumption is as derived in Chapter 2 using input-output based emissions accounting methods from WIOD data. The "visibility" score is again from Heffetz (2011).

Figure 3.3: Visibility and CO_2e intensity of consumption (2009)



Notes: Degree of "visibility" as defined by Heffetz (2011) based on survey responses. Average greenhouse gas intensity of consumption categories (kg of CO_2e per $), calculated in the same way as described in Chapter 2. Circle volume is proportional to average expenditure share among households. Expenditure data from the U.S. Consumer Expenditure Survey (CEX), 2009 cross-section. Line represents a linear least-square fit.

volume of each circle corresponds to mean household expenditure. It appears that "visible" types of consumption also tend to be more greenhouse gas intensive. A higher degree of status-seeking in an economy may thus skew consumption baskets towards higher levels of embedded carbon. However, the evidence in Figure 3.3 is merely suggestive and limited in a number of ways. Importantly, it presupposes that the degree of "visibility" as stated in the survey by Heffetz (2011) is an adequate measure of the intensity to which goods are subject to status-seeking. In addition, my estimates of the emissions content of different consumption goods is subject to a range of methodological limitations discussed in Chapter 2 of this thesis. Finally, my theoretical results are based on one status good and further assumptions would be needed to translate them into a setting with many goods subject to different degrees of status-seeking.

Still, the evidence presented above—in particular the concavity of Engel curves—suggests that status consumption increases under progressive income redistribution, unless status-relevance is sufficiently increasing in income. Given the higher emissions content of status goods, it seems likely that this would amplify rather than overturn the "equity-pollution dilemma".

For illustrative purposes, the graph does not show the categories "Utilities" and "Gasoline", which lie outside above the range of emissions intensities shown.

3.7 Conclusion

In this chapter I assess the relationship between income inequality and the demand for status goods. I propose a general formulation of status-seeking preferences where individual demand responds to a common reference level of consumption. I show that there exists a unique equilibrium under weak assumptions (Prop. 4) and discuss how a consumption reference level may itself be the long-run outcome of repeated pairwise comparisons.

I then explore the distributional comparative statics of aggregate positional consumption in such a model. This is motivated by claims and (mixed) empirical evidence that inequality may intensify status-seeking. I find that under the assumption of homogeneous consumers who take mean consumption as their reference level, status-seeking will simply reinforce the comparative statics implied by static Engel curves (Lemma 1). Status-seeking of that sort cannot then weaken, let alone overturn, the "equity-pollution" dilemma implied by concave Environmental Engel curves for CO_2 found in Chapter 2. On the contrary, it may well strengthen the dilemma as I find evidence of concave Engel curves for "visible" goods, which also tend to be more emissions intensive.

Meanwhile, when consumers have different weights in the reference level formation, a reversal is possible under conditions which I derive (Prop. 7). More generally, a complete ordering of income distributions by majorisation is only possible when status-relevance weights are a monotonic function of income. If that is not the case, it is impossible to claim any systematic relationship between inequality and aggregate positional consumption within the framework presented in this chapter. It is then also conceivable that status-seeking may overturn the "equity-pollution" dilemma.

In sum, for my model to support the claim that inequality fosters status-seeking, at least one of two conditions needs to hold: (i) status goods have convex Engel curves, or (ii) the status-relevance of individual consumers is increasing in income. As I show in Section 3.3, household expenditure patterns in the United States rather suggest that Engel curves for status goods are concave. Meanwhile, it is plausible that status-weights are increasing in income and, if this dynamic is strong enough, this may overturn the negative association between inequality and consumption of status goods implied by concave Engel curves. Whether this is true remains an open empirical questions.

Concluding remarks

Climate policy and economic inequality are related in a number of ways. The main contribution of this thesis as a whole is to improve our understanding of this relationship, which can go both ways and play out at different scales.

In Chapter 1 I have shown that the cost of carbon pricing may disproportionately fall on consumers in lower income countries with more emissions intensive value chains. While the distributional effects of climate policy within countries are often studied, my results suggest that further analysis of between-country effects can be fruitful. Depending on normative considerations, this may or may not be an argument against carbon pricing or for transfers to remedy such regressive price effects. Ultimately, this depends both on political considerations as well as the other costs and benefits of climate policy. In particular, further research may be necessary to contrast the consumer cost estimated in Chapter 1 with the global distribution of climate mitigation benefits and the potential use of carbon pricing revenue.

In Chapters 2 and 3, I have investigated the opposite direction of the inequality-environment relationship, which is far less studied. Within the United States, I have found that Environmental Engel curves for greenhouse gas emissions are upward-sloping and concave, suggesting an "equity-pollution dilemma". This dilemma may hold even when consumers are motivated by status, since I find that status goods also feature concave Engel curves and tend to be more carbon intensive. Depending on normative considerations, this may or may not be taken as an argument against income redistribution or for combined policies targeting emissions and inequality simultaneously. Further research may be necessary to quantify the "equity-pollution dilemma" at a global scale and test the assumptions underlying it. In particular, more work could aim to better understand the way status-seeking influences consumption and how it relates to levels of inequality.

Whichever conclusions one may wish to draw from the results presented in this thesis, I believe that they make clear the importance of considering both the distributional effects of climate policy as well as the consequences of income redistribution for consumer behaviour and the environment.

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Appendix A

Appendix to Chapter 1

A.1 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:

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

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

$$\hat{v}_h = \frac{\partial \log v(x_h, \mathbf{p})}{\partial \log x_h} \hat{\omega}_h \tag{A.2}$$

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

$$\begin{aligned}
\hat{\omega}_h &= \sum_{j=1}^{J} \left(-\hat{p}_j\right) s_{j,h} + \hat{x}_h \\
&= \sum_{j=1}^{J} \left(-\hat{p}_j\right) S_j + \qquad \sum_{j=1}^{J} \left(-\hat{p}_j\right) \left(s_{j,h} - S_j\right) + \qquad \hat{x}_h \\
&= \hat{W} + \qquad \hat{\psi}_h + \qquad \hat{x}_h
\end{aligned} \tag{A.3}$$

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

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

$$\hat{\psi}_h = -\left(\sum_{j=1}^{J} \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) \tag{A.4}$$

This finally gives the welfare change of consumer h as:

$$\hat{\omega}_h = \hat{W} - \left(\sum_{j=1}^{J} \beta_j \hat{p}_j\right) \log\left(\frac{x_h}{\tilde{x}}\right) + \hat{x}_h \tag{A.5}$$

A.2 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 relative to the old share would become:

$$\frac{S_{jk}^{new}}{S_{jk}} = (1+\tau\varepsilon_j)^{(1-\sigma_k)} \left(\frac{P_k^{new}}{P_k}\right)^{(\sigma_k - 1)} \tag{A.6}$$

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

$$c_{jk}^{new} = \frac{S_{jk}^{new}}{S_{jk}} \frac{P_k^{new}}{1+\tau\varepsilon_j} = \left(\frac{P_k^{new}}{1+\tau\varepsilon_j}\right)^{\sigma_k} c_{jk} \tag{A.7}$$

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 k used as intermediate inputs are the same as when k 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 $p_j = 1\ \forall j$. 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). But of course, the adjustments to input use will themselves change the structure of supply chains and, in consequence, the emissions intensities ε_k. 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 $1 + \tau\varepsilon_j^{new}$. I approximate this new structure numerically as described in Appendix A.3.

A.3 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 input requirements $\{c_{jk}^{new}\}$ when carbon price is levied on emissions intensities $\{\varepsilon_j\}$ based on original production $\{c_{jk}\}$
2. Calculate emissions intensities $\{\varepsilon_j^{new}\}$ based on adjusted production $\{c_{jk}^{new}\}$
3. Use new $\{\varepsilon_j^{new}\}$ to calculate further adjustment in production $\{c_{jk}^{new_2}\}$
4. Re-calculate $\{\varepsilon_j^{new_2}\}$ based on adjusted production $\{c_{jk}^{new_2}\}$
5. Back to step 1.

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

A.4 Parameter Robustness

Table A.1: Average estimates of income semi-elasticity by country

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

Notes: Average estimates of the income (semi)-elasticities as estimated from (1.16) and (1.17) for the WIOD cross-section 2004. Country averages across the 35 supply sectors each.

Table A.2: Average estimates of income and price elasticities by sector

	WIOD Sector	$\bar{\hat{\beta}}$	$\bar{\hat{\gamma}}$
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

Notes: Average estimates of the income (semi)-elasticities and price elasticities as estimated from (1.16) and (1.17) for the WIOD cross-section 2004. Sector averages across the 40 origin countries each.

Table A.3: Consistency of parameter estimates - $\hat{\beta}$

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

Notes: Pairwise correlations between 1400 income (semi)-elasticities as estimated from (1.16) and (1.17) for two yearly cross-sections of WIOD.

Table A.4: Consistency of parameter estimates - $\hat{\gamma}$

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

Notes: Pairwise correlations between 35 price elasticity parameters as estimated from (1.16) for two yearly cross-sections of WIOD.

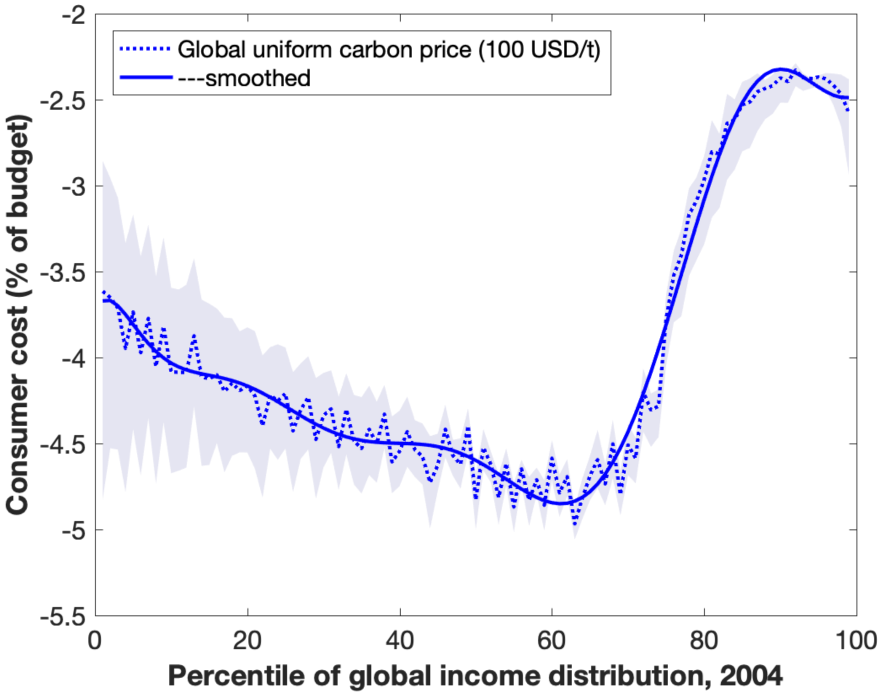
Table A.5: Consistency of parameter estimates - $\hat{\sigma}$

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

Notes: Pairwise correlations between 35 CES elasticities as estimated from (1.21) for two yearly cross-sections of WIOD.

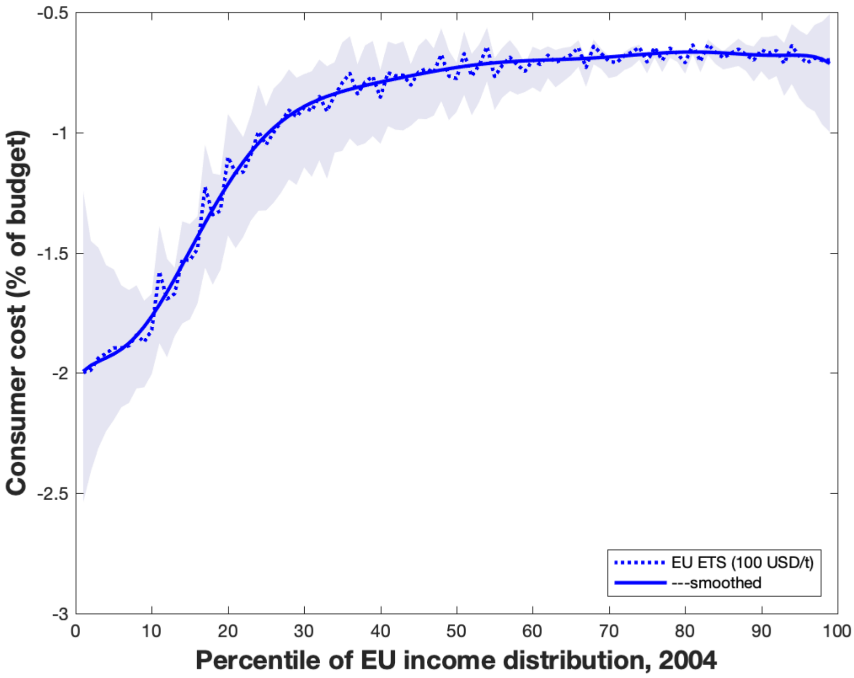
A.5 Alternative carbon price of 100 USD/t in 2004

Figure A.1: Global price of 100 USD/t - Global distribution of consumer cost



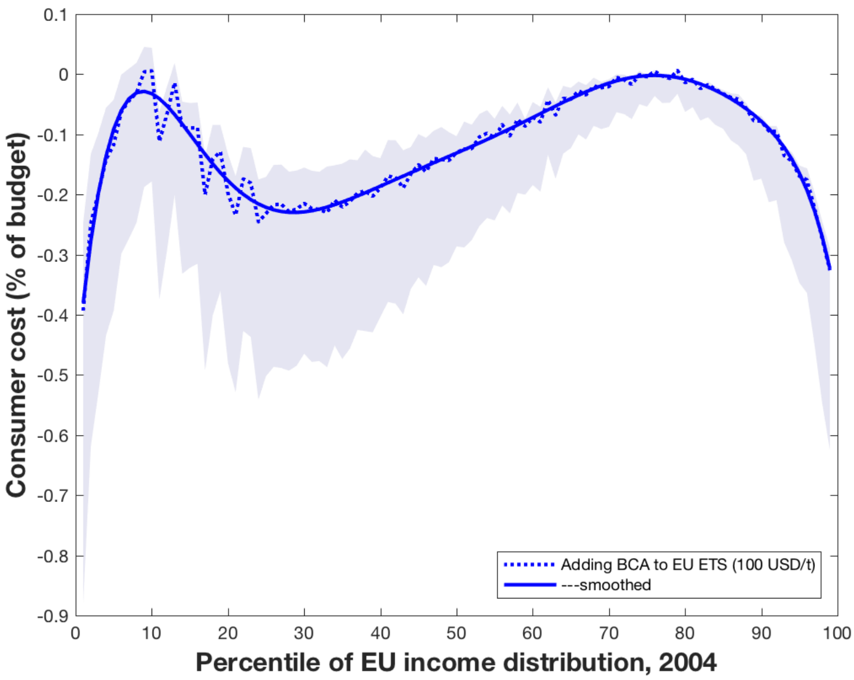
Notes: Same as Figure 1.2 but with a global uniform carbon price of 100 USD per ton of CO_2 simulated in 2004 (model includes 40 WIOD countries). Global distribution of the consumer cost under a global uniform carbon price. The horizontal axis shows percentiles of the income/expenditure distribution 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 (1.16), (1.17) and (1.21).

Figure A.2: EU price of 100 USD/t - EU distribution of consumer cost



Notes: Same as Figure 1.6 but with an EU-wide (27 countries, ETS sectors targeted) carbon price of 100 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 (1.16), (1.17) and (1.21).

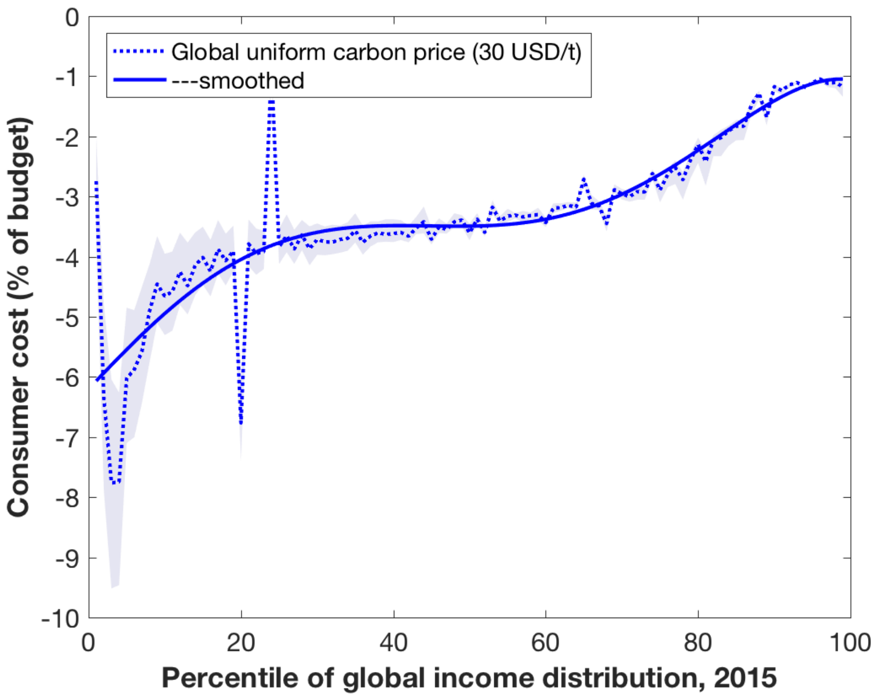
Figure A.3: EU BCA of 100 USD/t - EU distribution of consumer cost



Notes: Same as Figure 1.10 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). 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 (1.16), (1.17) and (1.21).

A.6 Carbon Price in 189 Countries (Eora) - 2015

Figure A.4: Global price of 30 USD/t - Global distribution of consumer cost (Eora)



Notes: 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 (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 (1.16), (1.17) and (1.21).

Appendix B

Appendix to Chapter 2

B.1 Estimation of emission content of consumption

I construct EECs following a standard input-output based emission accounting methodology, combining information on yearly expenditures of households on different consumption items (in $) with estimates of the carbon intensity of these different goods and services (kg of CO_2 per $). Total emissions z can be represented as two identities, depending on either total output $\mathbf{x}$ or final consumption expenditures $\mathbf{y}$:

$$z = \mathbf{x}'\mathbf{d} = \mathbf{y}'\mathbf{e}$$

I multiply final expenditures of household k (i.e. the vector $\mathbf{y_k}$ from the CEX data) with total emission intensities $\mathbf{e}$ to arrive at an estimate of the total emissions content of the consumption by household k:

$$z_k = \mathbf{y_k}'\mathbf{e}$$

To do so, I need estimates of the emissions intensity $\mathbf{e}$ per $ of final demand in each sector.

B.1.1 Input-output based emission factors

I allocate emissions intensities using information from the World Input-Output Tables (WIOD) is used. The 2013 release of WIOD contains information on 35 production sectors in 40 countries for the years 1996 through 2009. WIOD "Environmental Accounts" include information on total yearly emissions per sector (vector $\mathbf{z}$) and gross output per sector (vector $\mathbf{x}$). For a description of WIOD see Dietzenbacher et al. (2013) and Timmer et al. (2015). I use the information on 34 of the 35 WIOD sectors and exclude production in "Private Households", for which no emissions accounts exist. I first allocate to each sector a direct emissions intensity (kg of CO_2, CH_4, N_2O per $ of total output):

$$\mathbf{d} = \mathbf{z} \oslash \mathbf{x}$$

Here, $\oslash$ represents element-wise division. The input-output portion of WIOD then helps convert these into measures of total emissions intensity (vector $\mathbf{e}$). Total emissions intensity $\mathbf{e}$ captures the emission content of each unit of final demand $\mathbf{y}$ per industry, including all intermediate inputs from other sectors—output that is not used for final demand, but nevertheless requires economic activity and emissions. I construct three types of emission factors based on different assumptions regarding trade: (a) Closed economy, (b) Global supply-chain, but no trade; (c) Global supply-chain and trade.

Closed economy:

Throughout, I follow Leontief (1970), who proposed a linear relationship between the vector of total output in n sectors, $\mathbf{x}$, and the final demand from those n sectors, $\mathbf{y}$, of the form:

$$\mathbf{x} = \mathbf{C}\mathbf{x} + \mathbf{y}$$

Here, the $n \times n$ ($n = 34$ under the closed economy assumption) matrix $\mathbf{C}$ is called the "Direct Requirement matrix" and has element c_{ij}, which stands for the dollar amount of input from industry i necessary for the production of a dollar output from production j. In order to take account of secondary and higher-order relationships between input and output sectors, the "Direct Requirement matrix" $\mathbf{C}$ can be converted into the "Total Requirement matrix" $\mathbf{T}$. This matrix gives the dollar amount of output necessary from each sector j for a dollar of consumption in each sector i, taking into account all intermediate steps in the supply chain ad infinitum:

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

I then convert the vector of emissions intensities $\mathbf{d}$ into the vector of total emissions intensities $\mathbf{e}$:

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

A list of the 34 WIOD sectors used and their estimated emissions intensities for the years 1996 and 2009 is provided in Table B.1.

Global supply chain:

To account for the fact that US sectors obtain intermediate goods from productive sectors around the world, I also incorporate global input-output relations. With $m = 41$ countries (including "Rest of the World") and $n = 34$ sectors, the Direct Requirement matrix $\mathbf{C}$ is now of dimension $(mn \times mn) = (1394 \times 1394)$. We again obtain the Total Requirement matrix $\mathbf{T} = [\mathbf{I} - \mathbf{C}]^{-1}$. The vector of emissions intensities $\mathbf{d}^{\mathbf{World}}$ is now also of the dimension (1394×1) as is the vector of total emissions intensities $\mathbf{e}^{\mathbf{World}} = \mathbf{T}'\mathbf{d}^{\mathbf{World}}$. In a final step, I extract only the 34-element vector relating to the final demand of consumers in the United States, $\mathbf{e}^{\mathbf{US}}$, which now incorporates the emissions of intermediate goods supplied by the 34 sectors in all 41 countries.

Trade in final goods:

In a final step, I incorporate the fact that some of the final demand by consumers in the United States will be met through final goods imported from other countries. To do so, I use information on "final consumption expenditure by private households" contained in the WIOD input-output tables. Specifically, I construct a matrix $\mathbf{M}$, which has dimension $(m \times n) = (41 \times 34)$, where entry m_{ij} represents the share of final demand of US private households in sector j that is imported from country i (i.e. columns of $\mathbf{M}$ sum to 100%).

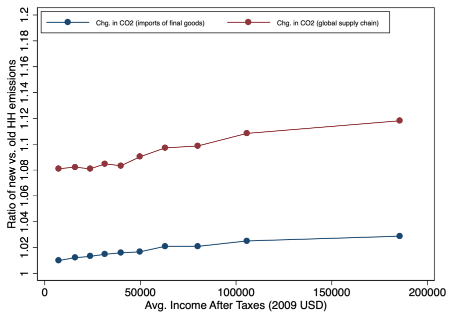
I then convert the vector of total emissions intensities $\mathbf{e}^{\mathbf{World}}$ to a matrix $\mathbf{E}^{\mathbf{World}}$ with dimensions $(n \times m) = (34 \times 41)$. The vector of emission intensities corresponding to final demand by US households, but incorporating the shares of final goods imported from other countries, is then given by:

$$\mathbf{e}^{\mathbf{Full}} = \operatorname{diag}\left(\mathbf{E}^{\mathbf{World}}\mathbf{M}\right)$$

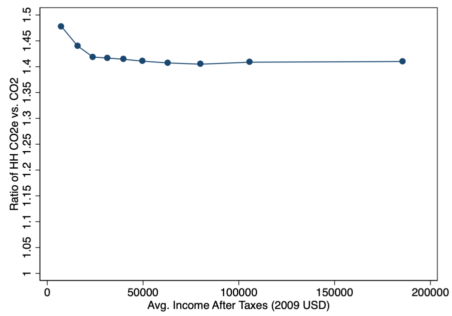
Figure B.1a shows adjustment factors when moving from the closed-economy assumption to a global supply chain and the inclusion of direct imports of final goods. Interestingly, the inclusion of trade has a larger relative impact on estimates of household carbon for those with higher incomes (e.g. an approximate 12% increase in CO_2 for the top decile when considering global supply chains compared to an 8% increase for households at the bottom decile).

Figure B.1: Comparison of emission measures (2009)

(a) Global supply chain & trade



(b) CO_2 vs. CO_2e (incl. CH_4, N_2O)



Notes: (a) Red = Average ratio of household CO_2 emissions when including global supply chain vs. closed economy assumption; Blue = Average ratio of household CO_2 emissions when including direct imports of final goods vs. all final goods from US production. Both by income deciles, 2009 CEX cross-section. (b) Average ratio of household total greenhouse gas emissions (CO_2e) vs. CO_2 emissions by income deciles. 2009 data.

B.1.2 Direct emission factors for high-carbon goods

To improve the precision of our estimates, I allocate emissions intensities to certain high-carbon consumption categories directly. Specifically, I do so for expenditures on home electricity, heating oil, natural gas, gasoline for car (incl. Diesel and motor oil), and air travel. Data on end consumer prices for electricity, heating oil, natural gas, and gasoline are provided by the U.S. Energy Information Administration (EIA, 2017). Emissions factors for gasoline, heating oil, natural gas, and kerosene are those used by the U.S. Environmental Protection Agency in guidelines for the Greenhouse Gas Inventory (EPA, 2009). Emission intensity of residential electricity is taken from the EPA's Emissions & Generation Resource Integrated Database (EPA, 2017). An overview of the resulting emission factors used is given in Table B.2. The implementation of direct emission factors for these consumption categories increases aggregate household carbon by about 25% (from 25.0t on average with only WIOD factors to 31.0t with added direct emission factors in 2009).

Emission factors for methane (CH_4) and nitrous oxide (N_2O):

I repeat the procedure described above for both CH_4 and N_2O. In a final step I then construct an aggregate measure for greenhouse gas content in consumption, converted into carbon dioxide equivalent scale, by multiplying emissions with their 100 year global warming potential multipliers reported in the IPCC AR5 report (Myhre et al., 2013). Figure B.1b depicts adjustment factors of that process.

B.2 Oaxaca-Blinder decomposition – Difference in means

In this paper we use Oaxaca-Blinder decomposition to decompose the change in average emission content of household consumption over time. The methodology was initially suggested to decompose wage differentials between population groups (Oaxaca, 1973; Blinder, 1973).

The decomposition method relies on coefficient estimates from a multiple linear regression analysis. It is assumed that expected emissions of household i in any year $m = 1996, \ldots, 2009$ have a linear form in k covariates:

$$y_i^m = \beta_0^m + \beta_1^m x_{1i}^m + \ldots + \beta_k^m x_{ki}^m + \varepsilon_i^m$$

The difference in means between two years, B (2009) and A (1996), can then be expressed as:

$$\begin{aligned}
\bar{y}^B - \bar{y}^A &= (\beta_0^B - \beta_0^A) + (\beta_1^B \bar{x}_1^B - \beta_1^A \bar{x}_1^A) + \ldots + (\beta_k^B \bar{x}_k^B - \beta_k^A \bar{x}_k^A) \\
&= G_0 + G_1 + \ldots + G_k
\end{aligned}$$

Here, then G_k is the contribution to the difference in means by the kth covariate. The contribution by each covariate k can then be further decomposed into three effects:

$$\begin{aligned}
G_k &= (\beta_k^B \bar{x}_k^B - \beta_k^A \bar{x}_k^A) = (\beta_k^B - \beta_k^A)\bar{x}_k^B + \beta_k^A(\bar{x}_k^B - \bar{x}_k^A) \\
&= \Delta\beta_k \bar{x}_k^B + \beta_k^A \Delta\bar{x}_k \\
&= \Delta\beta_k \bar{x}_k^A + \beta_k^A \Delta\bar{x}_k + \Delta\beta_k \cdot \Delta\bar{x}_k \\
&= C + E + CE
\end{aligned}$$

Here, C represents the difference due to changes in the coefficient of the k^{th} covariate, E represents the difference due to the difference in covariate means, and CE represents the interaction effect.

B.3 Factor decomposition of inequality

In this paper, I decompose the inequality in household carbon budgets using the regression-based approach suggested by Fields (2003) and building on factor decomposition initiated by Shorrocks (1982).

It is assumed that the expected carbon budget of household i in year m, y_i^m, is linear in k covariates:

$$y_i^m = \beta_0^m + \beta_1^m x_{1i}^m + ... + \beta_k^m x_{ki}^m + \varepsilon_i^m$$

Dropping year superscripts, the variance of household carbon budgets, $\sigma^2(y)$, is:

$$\sigma^2(y) = \sum_{j=1}^{k} \text{cov}\left[\beta_k x_k, y\right]$$

We then define the relative factor inequality weight of covariate k, $s_k(y)$, as:

$$s_k(y) = \frac{\text{cov}\left[\beta_k x_k, y\right]}{\sigma^2(y)}$$

This weight describes the contribution of the variation in the covariate k, in the variance of household emission budgets, $\sigma^2(y)$. Shorrocks (1982) has shown that under a number of assumptions, this decomposition will not only hold for the variance, but for any inequality measure $I(y)$ that is continuous, symmetric, and has $I(\mu, \mu, \ldots, \mu) = 0$. I carry out the decomposition using the STATA module from Fiorio and Jenkins (2007).

B.4 Results from emissions accounting

Table B.1: List of WIOD sectors

WIOD Code	WIOD Name	CO2 (kg/$, 1996)	CO2 (kg/$, 2009)	CH4 (g/$, 2009)	N2O (g/$, 2009)
15t16	Food, Beverages and Tobacco	0.71	0.49	11.55	0.73
17t18	Textiles and Textile Products	0.91	0.75	8.58	0.34
19	Leather, Leather and Footwear	0.77	0.56	10.42	0.5
20	Wood and Products of Wood and Cork	1.2	0.85	10.43	0.55
21t22	Pulp, Paper, Paper , Printing and Publishing	0.69	0.47	2.21	0.06
23	Coke, Refined Petroleum and Nuclear Fuel	2.27	0.94	23.26	0.03
24	Chemicals and Chemical Products	1.15	0.68	5.02	0.18
25	Rubber and Plastics	0.94	0.62	4.62	0.13
26	Other Non-Metallic Mineral	3.21	1.94	6.17	0.05
27t28	Basic Metals and Fabricated Metal	1.5	0.85	4.77	0.04
29	Machinery, Nec	0.71	0.57	3.68	0.04
30t33	Electrical and Optical Equipment	0.64	0.42	2.87	0.04
34t35	Transport Equipment	0.55	0.38	2.24	0.03
36t37	Manufacturing, Nec; Recycling	0.71	0.55	4.8	0.13
50	Motor Vehic. and Motorcyc.; Retail Sale of Fuel	0.32	0.17	0.94	0.01
51	Wholesale Trade and Commission Trade	0.21	0.09	0.49	0.01
52	Retail Trade; Repair of Household Goods	0.34	0.17	0.62	0.01
60	Inland Transport	1.07	0.79	9.63	0.03
61	Water Transport	2.94	1.98	5.2	0.1
62	Air Transport	1.77	1.48	4.95	0.07
63	Other Transport Activities; Travel Agencies	0.45	0.44	2.04	0.02
64	Post and Telecommunications	0.23	0.18	1.32	0.01
70	Real Estate Activities	0.21	0.06	0.38	0
71t74	Renting of M& Eq and Oth Business	0.26	0.14	0.95	0.01
AtB	Agriculture, Hunting, Forestry and Fishing	0.73	0.49	36.88	2.61
C	Mining and Quarrying	1.29	0.57	34.9	0.02
E	Electricity, Gas and Water Supply	7.93	5.42	10.54	0.09
F	Construction	0.57	0.38	4.06	0.04
H	Hotels and Restaurants	0.57	0.3	2.29	0.1
J	Financial Intermediation	0.17	0.09	0.58	0.01
L	Public Admin and Defence; Soc. Security	0.52	0.25	1.71	0.02
M	Education	0.56	0.35	1.17	0.03
N	Health and Social Work	0.36	0.17	0.85	0.02
O	Other Community, Social and Personal Services	0.43	0.18	8.59	0.04

Notes: List of 34 out of 35 WIOD sectors (excluding "Private Household"). Estimates for CO_2 content per USD output according to methodology described in Section 2.3 (1996 and 2009).

Table B.2: List of WIOD countries

Code	Country	Code	Country
AUS	Australia	JPN	Japan
AUT	Austria	KOR	Korea
BEL	Belgium	LVA	Latvia
BRA	Brazil	LTU	Lithuania
BGR	Bulgaria	LUX	Luxembourg
CAN	Canada	MLT	Malta
CHN	China	MEX	Mexico
CYP	Cyprus	NLD	Netherlands
CZE	Czech Republic	POL	Poland
DNK	Denmark	PRT	Portugal
EST	Estonia	ROM	Romania
FIN	Finland	RUS	Russia
FRA	France	SVK	Slovak Republic
DEU	Germany	SVN	Slovenia
GRC	Greece	ESP	Spain
HUN	Hungary	SWE	Sweden
IND	India	TWN	Taiwan
IDN	Indonesia	TUR	Turkey
IRL	Ireland	GBR	United Kingdom
ITA	Italy	USA	United States
RoW	Rest of World		

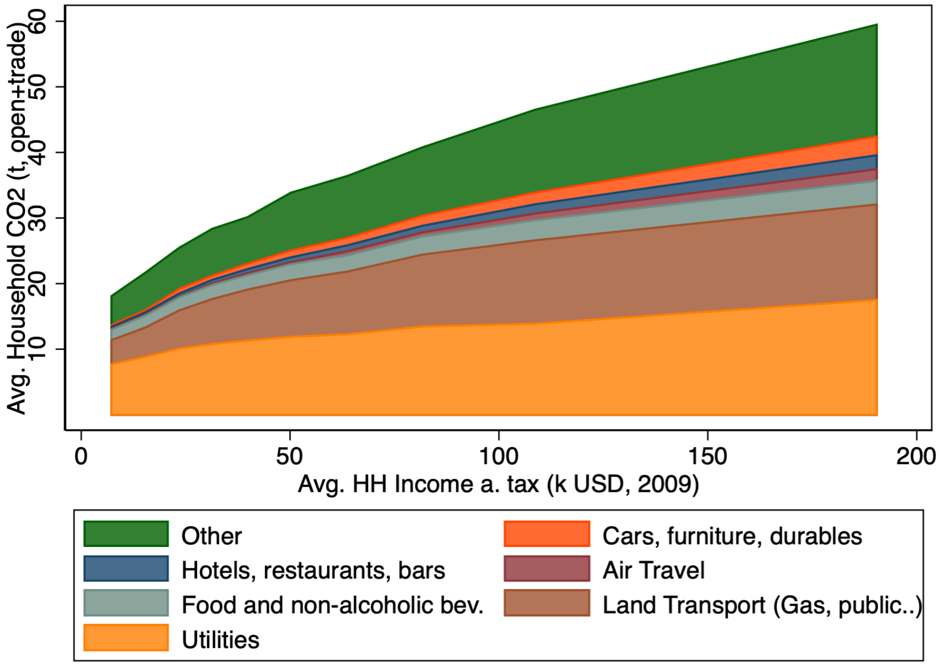
Notes: List of 41 WIOD countries (including "Rest of World").

Table B.3: Direct CO_2 emission factors (kg/$)

Year	Electricity	Gasoline	Heating fuel	Natural gas	Air travel
1996	8.67	7.14	9.26	7.82	2.14
1997	8.72	7.14	9.46	7.31	2.11
1998	8.61	8.29	11.09	7.32	1.99
1999	8.58	7.56	10.69	7.42	2.07
2000	8.45	5.84	6.85	6.4	1.81
2001	8.07	6.09	7.66	5.5	1.99
2002	8.16	6.41	8.26	6.35	2.07
2003	7.86	5.54	6.73	5.13	1.89
2004	7.61	4.69	5.65	4.68	1.92
2005	7.03	3.84	4.46	3.97	1.8
2006	6.3	3.39	4.23	3.85	1.65
2007	6.07	3.13	3.64	3.83	1.59
2008	5.57	2.69	3.26	3.46	1.51
2009	5.28	3.69	4.03	4.22	1.63

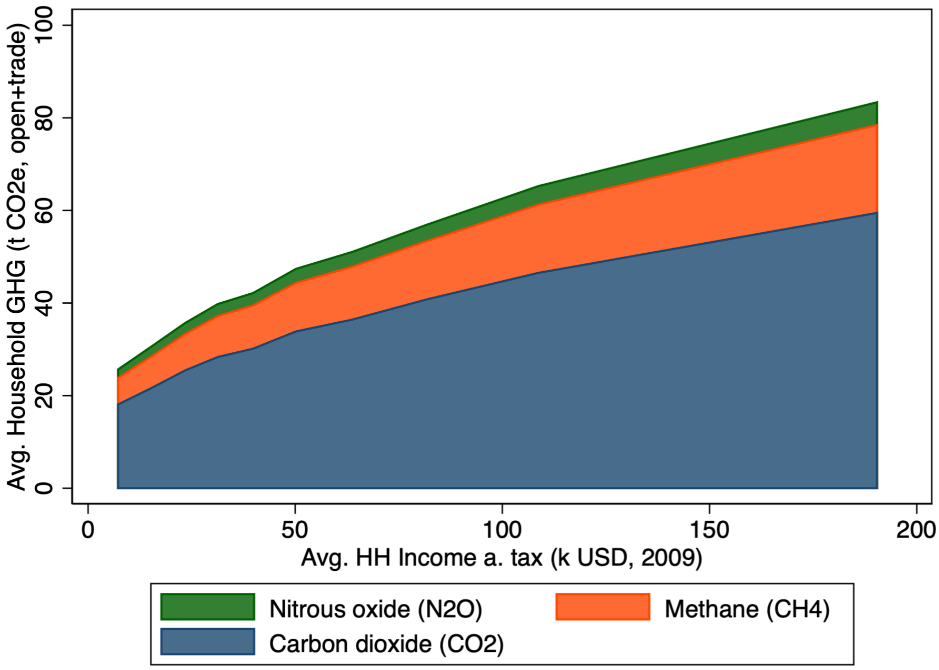
Notes: Based on annual average price data in the United States for residential electricity, gasoline, heating fuel, and natural gas (EIA); data on average air fares, passenger miles, and fuel consumption by US domestic airlines with revenue above $20m (BTS); constant CO_2 emission factors for gasoline, heating fuel, natural gas, and kerosene (EPA); yearly average emission intensity of electricity generation (EPA eGRiD).

Figure B.2: Carbon consumption breakdown (2009)



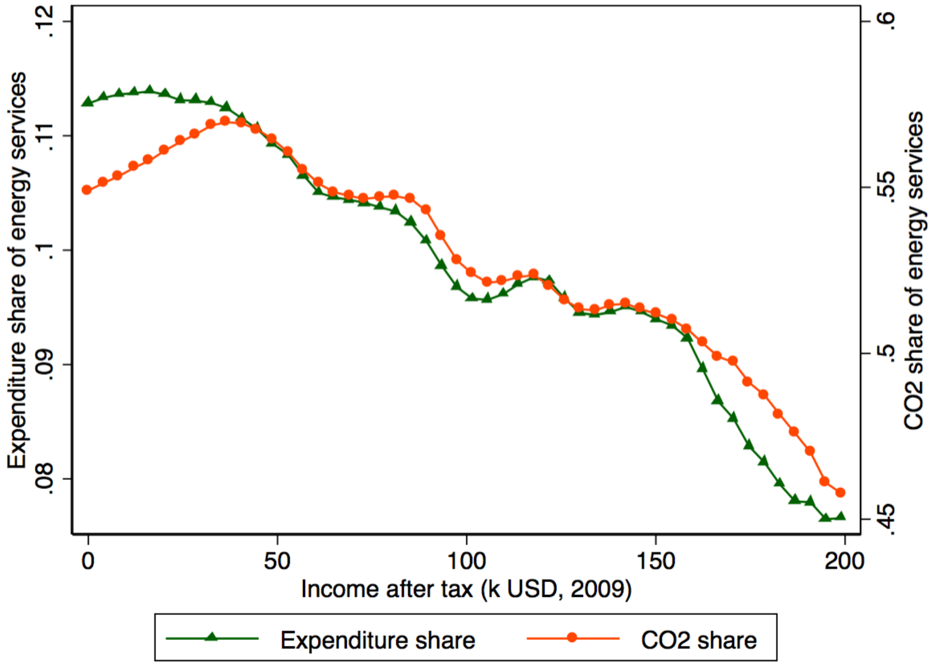
Notes: Decile averages of household income after tax (2009 USD) and estimated CO_2-content of consumption (current technology). Household weights as provided by CEX sample. Households with reported after-tax income below $0 and above $400K excluded.

Figure B.3: Greenhouse gas breakdown (2009)



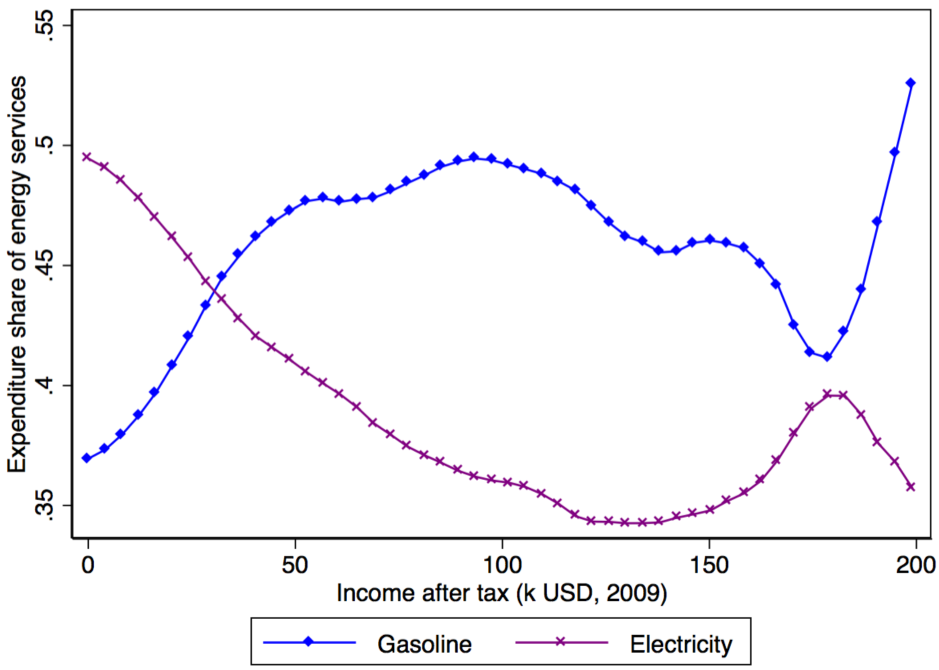
Notes: Decile averages of household income after tax (2009 USD) and estimated GHG-content of consumption (current technology). Household weights as provided by CEX sample. Households with reported after-tax income below $0 and above $400K excluded.

Figure B.4: Energy services - Share in expenditure / CO_2 (2009)



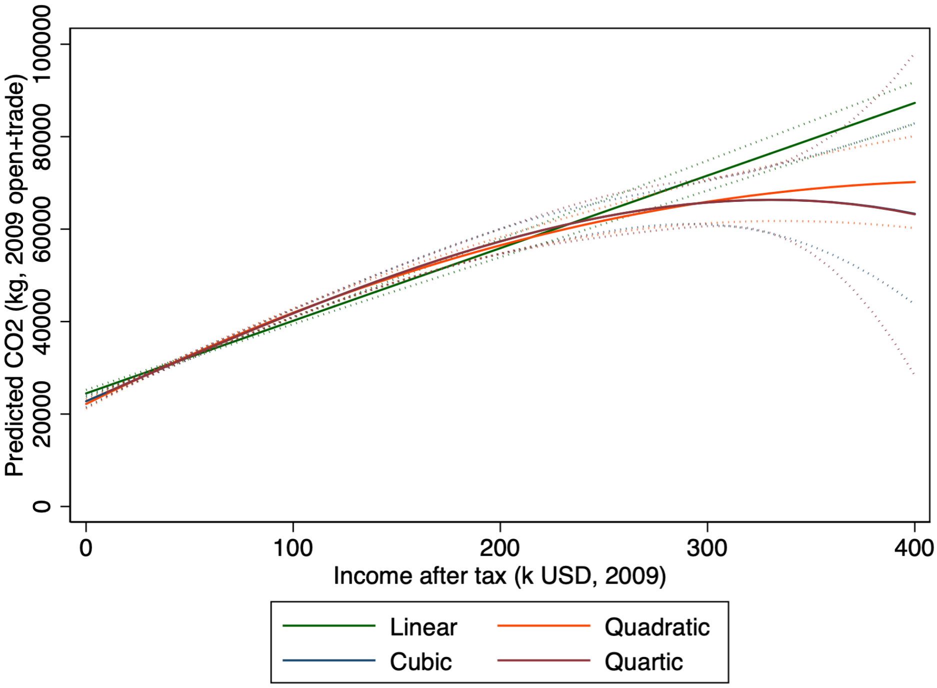
Notes: Household total expenditure on energy services (air travel, electricity, gasoline, heating fuel, natural gas) as share of total expenditures (left axis) and CO_2 emissions related to energy services as share in CO_2 emissions in total consumption expenditures (right axis); both as a function of income after tax (2009 USD). Kernel-weighted local polynomial fit (Epanechnikov, bandwith=7.52). Households with reported after-tax income below $0 and above $200 k excluded.

Figure B.5: Electricity & gasoline - Share in energy expenditure (2009)



Notes: Household expenditure on individual energy services (electricity and gasoline) as share of total expenditure on energy services (air travel, electricity, gasoline, heating fuel, natural gas); both as a function of income after tax (2009 USD). Kernel-weighted local polynomial fit (Epanechnikov, bandwith=7.94). Households with reported after-tax income below $0 and above $200K excluded.

Figure B.6: Engel curves - Quadratic vs. higher-order polynomial (2009)



Notes: Fitted values of multiple linear regression models including polynomial terms (of orders 1 through 4) for income after tax. Covariates are family size, family size (squared), age of HH head, age (squared), marital status, education, race, region. Dotted lines mark 95% confidence intervals using heteroscedasticity robust standard errors.

Appendix C

Appendix to Chapter 3

C.1 Visible consumption categories

Table C.1: Consumption categories and their "visibility".

Consumption category			Visibility
Food home	c1	FdH	0.51
Food out	c2	FdO	0.62
Cigarettes	c3	Cig	0.76
Alcohol home	c4	AlH	0.61
Alcohol out	c5	AlO	0.60
Clothing	c6	Clo	0.71
Laundry	c8	Lry	0.34
Jewelry	c9	Jwl	0.67
Barbers etc.	c10	Brb	0.60
Rent/home	c11	Hom	0.50
Hotels etc.	c12	Htl	0.46
Furniture	c13	Fur	0.68
Home utilities	c14	Utl	0.31
Home phone	c15	Tel	0.30
Home insurance	c17	HIn	0.17
Health care	c18	Med	0.36
Legal fees	c19	Fee	0.26
Life insurance	c20	LIn	0.16
Cars	c21	Car	0.73
Car repair	c22	CMn	0.42
Gasoline	c23	Gas	0.39
Car insurance	c24	CIn	0.23
Public transportation	c25	Bus	0.45
Air travel	c26	Air	0.46
Books etc.	c27	Bks	0.57
Recreation 1	c28	Ot1	0.66
Recreation 2	c29	Ot2	0.58
Education	c30	Edu	0.56
Charities	c31	Cha	0.34

Notes: "Visibility" based on a survey of 480 respondents by Heffetz (2011), ranking each consumption category based on the following question: *"Imagine that you meet a new person who lives in a household similar to yours. Imagine that their household is not different from other similar households, except that they like to, and do, spend more than average on [jewelry and watches]. Would you notice this about them, and if so, for how long would you have to have known them, to notice it? Would you notice it almost immediately upon meeting them for the first time, a short while after, a while after, only a long while after, or never?"* Answers are coded from 1 (almost immediately) to 5 (never) and the index is the average response for each category, scaled by $(x-1)/4$ to range between 0 and 1. In addition to the 29 categories listed, Heffetz (2011) also elicit "visibility" for two additional categories, "underwear" and "mobile phones", which are not used in this paper. The survey was carried out by telephone in the United States between May 2004 and January 2005.

C.2 Examples

C.2.1 Example 1: "KUJ" status-seeking

The following is an example of status-seeking with a simple mean reference level from Section 3.4 and a generalisation of preferences proposed in Bowles and Park (2005). Consumer i chooses to divide income m_i between two goods (positional x and non-positional y) in a way equivalent to the following maximisation problem:

$$\begin{aligned} \max_{x_i,y_i} U_i &= u(\widehat{x_i}, y_i), \\ \text{s.t. } p_x x_i + p_y y_i &\leq m_i, \\ \widehat{x_i} &= x_i - \delta_{i,x}\bar{x}_i, \\ 0 &\leq \delta_{i,x} < 1 \end{aligned} \tag{C.1}$$

Let us further assume that $\frac{\partial U}{\partial \widehat{x}} = U_{\widehat{x}} > 0$, $U_y > 0$, $U_{yy} < 0$, $U_{\widehat{x}\widehat{x}} < 0$, and $U_{\widehat{x}y} > 0$. Preferences are strictly monotonic and convex. Status-seeking is embodied by the relative discounting of personal consumption x_i by the personal reference level $\bar{x}_i$ weighted by parameter $\delta_{i,x}$ which describes the importance of status. We further assume that consumers have homothetic preferences in the absence of status-seeking (i.e. when $\delta_{i,x} = 0$). Let us normalise prices of both goods, so that x_i and y_i can be understood as expenditure levels. Finally, denote as $x_i^*(m_i)$ the demand for x in absence of status competition ($\delta_{i,x} = 0$) and the corresponding expenditure share as $\lambda_x^* = \frac{x_i^*(m_i)}{m_i}$, which is constant across income levels. Consumers i with income m_i and reference level $\bar{x}_i$ will choose consumption as follows:

$$\begin{gathered} x_i(m_i;\bar{x}_i) = \lambda_x^* m_i + (1-\lambda_x^*)\delta_{i,x}\bar{x}_i \ \ \& \ \ y_i(m_i;\bar{x}_i) = m_i - x_i(m_i;\bar{x}_i) \\ \text{given that } m_i \geq \delta_{i,x}\bar{x}_i \ \forall i \end{gathered} \tag{C.2}$$

The second condition ensures affordability of the unique interior optimum. Expenditure on positional good x is increasing in status-relevance $\delta_{i,x}$ and the reference level $\bar{x}_i$. Assume a continuum of consumers, represented by the atomistic income distribution $F(m)$:

$$m_{LO} \leq m \leq m_{HI},\ F(m_{LO}) = 0,\ F(m_{HI}) = 1,\ 0 \leq f(m) \leq 1 \tag{C.3}$$

Finally, assume that all consumers have the same reference level, mean consumption level $\bar{x}$, but that status-relevance for consumer i depends on income, i.e. we have $\delta_x(m_i)$. At an interior optimum, individual choice is:

$$\begin{gathered} x(m_i,\bar{x}) = \lambda_x^* m_i + (1-\lambda_x^*)\delta_x(m_i)\bar{x} \\ \text{given that } m_i \geq \delta_x(m_i)\bar{x} \ \forall i \end{gathered} \tag{C.4}$$

In the unique symmetric equilibrium, and assuming that all consumers can afford it (i.e. $m_i \geq \delta_x(m_i)\overline{x}\; \forall\; i$), (mean) consumption of positional good x is:

$$\overline{x} = \frac{1}{1-(1-\lambda_x^*)\overline{\delta}}\lambda_x^*\overline{m} \tag{C.5}$$

Aggregate positional consumption $\overline{x}$ is proportional to aggregate income $\overline{m}$. “Over-consumption” (relative to $\overline{x}^* = \lambda_x^*\overline{m}$) is increasing in aggregate status-relevance ($\overline{\delta}$) and decreasing in the budget share of x unrelated to status (λ_x^*). This leads to the following comparative statics with respect to changes in the income distribution.

Proposition 8 *When status-relevance is decreasing, but decreasingly so ($\delta'' \geq 0$), we can state that for two income distributions $F_A(m)$ and $F_B(m)$, where $F_A(m) \succ_{SO} F_B(m)$, it is true that $\overline{\delta}_A \leq \overline{\delta}_B$ and thus $0 \leq \overline{x}_A \leq \overline{x}_B$.*

Proof. Direct translation of the equivalence result of Hadar and Russell (1969) on expected utilities and second-order stochastic dominance. We have two income distributions $F_A(m)$, $F_B(m)$, with $F_A(m) \succ_{SO} F_B(m)$, and a continuous function $\delta(m)$ characterised by $\delta'(m) < 0$ and $\delta''(m) > 0$. The difference between $\overline{\delta}_A$ and $\overline{\delta}_B$ is:

$$\overline{\delta}_A - \overline{\delta}_B = \int_{m_{LO}}^{m_{HI}} \delta(m)\,[f_A(m) - f_B(m)]\,dx$$

Twice integrating by parts gives:

$$\begin{aligned}
\overline{\delta}_A - \overline{\delta}_B &= \lfloor \delta(m)\,[F_A(m) - F_B(m)] \rfloor_{m_{LO}}^{m_{HI}} - \int_{m_{LO}}^{m_{HI}} \delta'(m)\,[F_A(m) - F_B(m)]\,dx \\
&= \left\lfloor -\delta'(m) \int_{m_{LO}}^{m} [F_A(y) - F_B(y)]\,dy \right\rfloor_{m_{LO}}^{m_{HI}} + \int_{m_{LO}}^{m_{HI}} \delta''(m) \int_{m_{LO}}^{m} [F_A(y) - F_B(y)]\,dydm
\end{aligned}$$

From second-order dominance we know the following:

$$F_A(m) \succ_{SO} F_B(m) \;\rightarrow\; \int_{m_{LO}}^{m} [F_A(y) - F_B(y)]\,dy \leq 0\; \forall m_{LO} \leq m \leq m_{HI}$$

Given that $\delta(m)$ is decreasing and convex, this concludes the proof:

$$\delta'(m) < 0\; \&\; \delta''(m) > 0\; \forall m_{LO} \leq m \leq m_{HI} \;\rightarrow\; \overline{\delta}_A - \overline{\delta}_B \leq 0$$

■

This is simply a special case of Proposition 5. $\delta'' \geq 0$ results in convex Engel curves despite otherwise homothetic preferences and second-order dominance is necessary for majorisation of discrete income distributions, in the sense that $\mathbf{m_B} \succ_m \mathbf{m_A}$ implies that $F_A(m) \succ_{SO} F_B(m)$ (as discussed in e.g. Egozcue and Wing-Keung, 2010).

C.2.2 Example 2: "Trickle-down" status-seeking

Continuing the simplified example from Appendix C.2.1, I now demonstrate some results under the alternative regime of status-seeking which leads to *trickle-down* consumption. I define "upward-referencing" status-seeking as a situation where the reference level $\bar{x}_i$ of consumer i is only affected by the consumption of those consumers j with $m_j \geq m_i$. I now assume a constant degree of status-relevance across incomes, i.e. $\delta_x(m_i) = \delta_x \; \forall \; m_i$. I further assume that each consumer faces a personal reference level, defined as the mean consumption of x by those better off than her, i.e. $\bar{x}_i = \frac{\int_{m_i}^{m_{HI}} x(m) f(m) dm}{1-F(m_i)}$. Again assuming affordability of the interior optimum, a consumer then chooses the following consumption of x:

$$\begin{aligned} x(m_i, \bar{x}_i) &= \lambda_x^* m_i + (1-\lambda_x^*)\delta_x \int_{m_i}^{m_{HI}} x(m) f(m) dm \\ &\text{given that } m_i \geq \delta_x \bar{x}_i \; \forall i \end{aligned} \tag{C.6}$$

Aggregate behaviour is no longer characterised by an equilibrium, as the set of those affecting a consumer's reference level is disjoint from the set of those affected by her consumption. Instead, choices can be derived by iteration downwards starting with the highest income consumer, whose choices are not distorted by status-seeking, giving rise to the "expenditure cascades" found by Frank et al. (2014).

While a general solution will depend on the specific shape of $F(m)$ along the entirety of its domain, we can derive a result for aggregate consumption of x for those portions of the income distribution which can be approximated by a Pareto distribution.

Definition 3 *An income distribution is Pareto distributed above m_{LO} when $P[m > \hat{m}] = 1 - F(\hat{m}) = \hat{m}^{-\frac{1}{\eta}}$ for all $m_{LO} \leq \hat{m} < \infty$ and $0 < \eta \leq 1$.*

Income distributions are oftentimes well approximated by a Pareto distribution, especially in upper tails. Following Jones (2015), I call η the "Pareto inequality measure" and limit it to $0 < \eta < 1$. A property of the Pareto distribution is that conditional expected values above a cut-off point are proportional to said cut-off by $\alpha = \frac{1}{1-\eta}$, yielding the relation:

$$E[m|m > m_i] = \frac{1}{1-\eta} m_i = \alpha m_i \; \forall \; m_i \geq m_{LO} \; \& \; 0 < \eta < 1 \tag{C.7}$$

The optimal choice of consumer i with income m_i is then given by:

$$x(m_i) = \frac{1}{1-(1-\lambda_x^*)\delta\alpha} \lambda_x^* m_i \; \rightarrow \; \bar{x} = \frac{1}{1-(1-\lambda_x^*)\delta\alpha} \lambda_x^* \overline{m} \tag{C.8}$$

Proposition 9 *When status-seeking is "upward-referencing" and income distributed according to a Pareto distribution with constant α, aggregate consumption of positional good x is increasing in the inequality of income in the sense that $\frac{d\bar{x}}{d\eta} > 0$.*

Proof. Income is continuously distributed according to a Pareto distribution with Pareto measure $0 < \eta < 1$ above the minimum income m_{LO}, so that:

$$F(m) = 1 - \left(\frac{m}{m_{LO}}\right)^{-\frac{1}{\eta}} \quad \forall m \geq m_{LO} \text{ and } f(m) = \frac{1}{\eta}\left(\frac{m}{m_{LO}}\right)^{-\frac{1}{\eta}-1} \quad \forall m \geq m_{LO}$$

For any income-level $m_i \geq m_{LO}$, the mean of m above that income is:

$$\begin{aligned} E[m|m \geq m_i] &= \frac{\int_{m_i}^{\infty} m f(m) dm}{1 - F(m_i)} = \frac{\int_{m_i}^{\infty} \frac{1}{\eta} m^{-\frac{1}{\eta}} dm}{m_i^{-\frac{1}{\eta}}} = \frac{[-\frac{1}{\eta-1} m_i^{-\frac{1}{\eta}+1}]_{m_i}^{\infty}}{m_i^{-\frac{1}{\eta}}} \\ &= \frac{\frac{1}{1-\eta} m_i^{-\frac{1}{\eta}+1}}{m_i^{-\frac{1}{\eta}}} = \frac{1}{1-\eta} m_i = \alpha m_i \end{aligned}$$

At the interior optimum, the expenditure share on positional good x for consumer i is homogeneous of degree 0 in $\bar{x}_i$ and m_i:

$$\begin{aligned} \lambda_{i,x}(m_i;\bar{x}_i) &= \frac{x_i(m_i;\bar{x}_i)}{m_i} = \lambda_x^* + (1-\lambda_x^*)\delta_{i,x}\frac{\bar{x}_i}{m_i} \\ \rightarrow \lambda_{i,x}(m_i;\bar{x}_i) &= \lambda_{i,x}(\alpha m_i; \alpha \bar{x}_i) \end{aligned}$$

All consumers choose the same expenditure share $\lambda_x = \lambda_{i,x}(m_i;\bar{x}_i)$. This yields:

$$\begin{aligned} \lambda_x &= \lambda_x^* + (1-\lambda_x^*)\delta_{i,x}\frac{\bar{x}_i}{m_i} \\ &= \lambda_x^* + (1-\lambda_x^*)\delta_{i,x}\alpha\lambda_x \\ \lambda_x &= \frac{1}{1-(1-\lambda_x^*)\delta\alpha}\lambda_x^* \end{aligned}$$

■

For this admittedly special case, we can thus say that the "overconsumption" of positional good x arising from status-seeking is increasing in both status-relevance (δ) and Pareto inequality (η). As status-seeking is "upward-referencing" this result will carry through even when only a portion of the income distribution is Pareto distributed, as long as η is constant from that portion upwards. This is thus an alternative dynamic, which can explain the responsiveness of positional consumption to changes in top income shares found by Frank et al. (2014) and Betrand and Morse (2016).

C.3 Proofs

C.3.1 Proof of Proposition 4

Existence: For a given $\mathbf{m} \in M^N$, $f(\mathbf{m},r)$ is a function of a single variable r. Based on Brouwer's fixed-point theorem (e.g. Kakutani, 1941), if (A1') $f(\mathbf{m},r)$ maps to congruent domains in the remaining dimension, i.e. $f : R \to R$, and if (A2') $f(\mathbf{m},r)$ is continuous in r, then at least one fixed-point exists where $r = f(\mathbf{m},r)$.

A1': In the case of consumption of a divisible good x with price p_x, the consumption of each individual is limited to the interval $x_i \in [0, \frac{m_i}{p_x}]$, and thus the weighted arithmetic mean of consumption level ($\sum_{i=1}^{N} \alpha_i = 1$ and $\alpha_i \geq 0 \ \forall \ i$) is limited to the interval $r \in [0, \frac{m_{max}}{p_x}]$.

A2': $\sum_{i=1}^{N} \alpha_i x(m_i,r)$ is continuous in r since $x(m_i,r)$ is continuous in r.

Uniqueness: Based on the contraction mapping theorem by Banach (e.g. Ciric, 1974), $f : R \to R$ has a unique and stable fixed-point if (B1) f is a contraction mapping.

B1': For any given $\mathbf{m} \in M^N$, f is represented by the continuously differentiable (C^1) function $f(\mathbf{m},r)$. Then it is sufficient that $|\frac{\partial f(\mathbf{m},r)}{\partial r}| < 1$ for f to be a contraction mapping. This is again true since we assume status competition which is not "destructive" ("Social Monotonicity"), i.e. $0 \leq \frac{\partial x(m,r)}{\partial r} < 1 \ \forall m \in M$, because $\frac{\partial f(\mathbf{m},r)}{\partial r} = \sum_{i=1}^{N} \alpha_i \frac{\partial x(m_i,r)}{\partial r}$.

C.3.2 Proof of Lemma 1

Proof by contradiction in two parts:

(1) Let us assume that $(\bar{x}(\mathbf{m}_B,r_A) - \bar{x}(\mathbf{m}_A,r_A)) > 0$ and $(\bar{x}(\mathbf{m}_B,r_B) - \bar{x}(\mathbf{m}_A,r_A)) < 0$. Equivalently $(f(\mathbf{m}_B,r_A) - f(\mathbf{m}_A,r_A)) > 0$ and $(f(\mathbf{m}_B,r_B) - f(\mathbf{m}_A,r_A)) < 0$. The latter can be re-written as $r_B = f(\mathbf{m}_B,r_B) < r_A = f(\mathbf{m}_A,r_A)$. We then have that $f(\mathbf{m}_B,r_A) = f(\mathbf{m}_B,r_B) + \int_{r_B}^{r_A} \frac{\partial f(\mathbf{m}_B,r)}{\partial r} dr$. Since $\frac{\partial f(\mathbf{m}_B,r)}{\partial r} < 1$, we have $f(\mathbf{m}_B,r_A) < f(\mathbf{m}_B,r_B) + (r_A - r_B)$ and thus $f(\mathbf{m}_B,r_A) < r_A = f(\mathbf{m}_A,r_A)$ which is a contradiction.

(2) Let us assume that $(\bar{x}(\mathbf{m}_B,r_A) - \bar{x}(\mathbf{m}_A,r_A)) < 0$ and $(\bar{x}(\mathbf{m}_B,r_B) - \bar{x}(\mathbf{m}_A,r_A)) > 0$. Equivalently $(f(\mathbf{m}_B,r_A) - f(\mathbf{m}_A,r_A)) < 0$ and $(f(\mathbf{m}_B,r_B) - f(\mathbf{m}_A,r_A)) > 0$. The latter can be re-written as $r_B = f(\mathbf{m}_B,r_B) > r_A = f(\mathbf{m}_A,r_A)$. We then have that $f(\mathbf{m}_B,r_A) = f(\mathbf{m}_B,r_B) - \int_{r_A}^{r_B} \frac{\partial f(\mathbf{m}_B,r)}{\partial r} dr$. Since $\frac{\partial f(\mathbf{m}_B,r)}{\partial r} < 1$, we have $f(\mathbf{m}_B,r_A) > f(\mathbf{m}_B,r_B) - (r_B - r_A)$ and thus $f(\mathbf{m}_B,r_A) > r_A = f(\mathbf{m}_A,r_A)$ which is a contradiction.

C.3.3 Proof of Proposition 5

Sufficiency: As $\mathbf{m_A} \succ_m \mathbf{m_B}$, $\mathbf{m_B}$ can be arrived at from (a permutation of) $\mathbf{m_A}$ through a finite number of Pigou-Dalton transfers from j to i, where $m_i < m_j$. From $\frac{\partial^2 x(m,r)}{\partial m^2} < (>)0\ \forall m, r \in M \subset \mathbb{R}_+$, we have $\left(\frac{\partial x(m_i,r_A)}{\partial m} - \frac{\partial x(m_j,r_A)}{\partial m}\right) > (<)0$ and thus $[\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)] > (<)0$ for any small enough transfer Δ. By Lemma 1, this also implies $[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] > (<)0$.

Necessity: Let us suppose that $x(m,r)$ is neither strictly concave nor strictly convex over m (but also not linear). Then $\exists \mathbf{m_A}$ and (i,j,k) s.t.$m_j > m_i$, $m_k > m_i$ and $\frac{\partial x(m_j,r)}{\partial m} > (<)\frac{\partial x(m_i,r)}{\partial m}$ but $\frac{\partial x(m_k,r)}{\partial m} \leq (\geq)\frac{\partial x(m_i,r)}{\partial m}$. Call respectively $\mathbf{m_B}$ and $\mathbf{m'_B}$ the distributions arising from $\mathbf{m_A}$ after a small transfer Δ from j to i and k to i respectively. By Lemma 1, we have $[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] < (>)0$ but $[\bar{x}(\mathbf{m'_B}, r'_B) - \bar{x}(\mathbf{m_A}, r_A)] \geq (\leq)0$. This is so despite $\mathbf{m_A} \succ_m \mathbf{m_B}$ and $\mathbf{m_A} \succ_m \mathbf{m'_B}$. Finally, when $x(m,r)$ is linear in m, we have $\frac{\partial x(m_i,r)}{\partial m} = \frac{\partial x(m_j,r)}{\partial m} = \frac{\partial x(m_k,r)}{\partial m}$ and thus $[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] = \bar{x}(\mathbf{m'_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] = 0$

C.3.4 Proof of Proposition 6

We consider two scenarios when $f(\mathbf{m}_B, r_A) \neq f(\mathbf{m}_A, r_A)$:

(1) Let us assume that $f(\mathbf{m}_B, r_A) > f(\mathbf{m}_A, r_A)$. By Lemma 1, we have $r_B = f(\mathbf{m}_B, r_B) > f(\mathbf{m}_A, r_A) = r_A$. Thus $f(\mathbf{m}_B, r_B) = f(\mathbf{m}_B, r_A) + \int_{r_A}^{r_B} \frac{\partial f(\mathbf{m}_B,r)}{\partial r} dr$. Finally, because $\frac{\partial f(\mathbf{m}_B,r)}{\partial r} > 0$, this gives $f(\mathbf{m}_B, r_B) > f(\mathbf{m}_B, r_A)$ and thus $(f(\mathbf{m}_B, r_B) - f(\mathbf{m}_A, r_A)) > (f(\mathbf{m}_B, r_A) - f(\mathbf{m}_A, r_A))$.

(2) Let us assume that $f(\mathbf{m}_B, r_A) < f(\mathbf{m}_A, r_A)$. By Lemma 1, we have $r_B = f(\mathbf{m}_B, r_B) < f(\mathbf{m}_A, r_A) = r_A$. Thus $f(\mathbf{m}_B, r_B) = f(\mathbf{m}_B, r_A) - \int_{r_B}^{r_A} \frac{\partial f(\mathbf{m}_B,r)}{\partial r} dr$. Finally, because $\frac{\partial f(\mathbf{m}_B,r)}{\partial r} > 0$, this gives $f(\mathbf{m}_B, r_B) < f(\mathbf{m}_B, r_A)$ and thus $(f(\mathbf{m}_B, r_B) - f(\mathbf{m}_A, r_A)) < (f(\mathbf{m}_B, r_A) - f(\mathbf{m}_A, r_A))$.

C.3.5 Proof of Proposition 7

We consider a linear approximation of the effect of a small enough transfer Δ from j to i on aggregate positional consumption:

$$\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A) \approx \left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m} \right) \Delta + \sum_{k=1}^{N} \frac{\partial x(m_k, r_A)}{\partial r} \frac{\partial r}{\partial \Delta} \Delta$$

The first portion of this effect is the direct change in consumption by i and j, the second portion is the reaction of all consumers to the change in reference level due to the transfer. We further linearly approximate the second portion of this to give:

$$\frac{\partial r}{\partial \Delta} \approx \Phi(\mathbf{m}, r_A) \left(\alpha_i \frac{\partial x(m_i, r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j, r_A)}{\partial m} \right)$$

Above, Φ stands in for the degree to which the social feedback mechanism magnifies any initial change in reference level via iterated adjustments that finally settle in the new reference-level equilibrium. It will be larger the stronger is $\frac{df(\mathbf{m},r)}{dr}$, i.e. the steeper the function $f(.)$ in Figure 3.2. Approximating $f(.)$ linearly around r_A, the multiplier is:

$$\Phi(\mathbf{m}, r_A) \approx \frac{1}{1 - \frac{\partial f(\mathbf{m}, r_A)}{\partial r}}$$

Let us now show that for both Case A and Case B in Proposition 7, we will have that $\text{sign}[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] \neq \text{sign}[\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)]$.

Case A:

$$0 < \left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right) < -\Psi(\mathbf{m}, r_A)\left(\alpha_i \frac{\partial x(m_i, r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j, r_A)}{\partial m}\right)$$

$$0 < \left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right)$$
$$\rightarrow \exists \varepsilon > 0 \text{ s.t. } [\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)] > 0 \; \forall \; \Delta \in (0, \varepsilon)$$

$$\left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right) < -\Psi(\mathbf{m}, r_A)\left(\alpha_i \frac{\partial x(m_i, r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j, r_A)}{\partial m}\right)$$
$$\rightarrow \exists \gamma > 0 \text{ s.t. } [\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] < 0 \; \forall \; \Delta \in (0, \gamma)$$
$$\Rightarrow \text{sign}[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] \neq \text{sign}[\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)] \; \forall \Delta \in (0, \min\{\varepsilon, \gamma\})$$

Case B:

$$0 > \left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right) > -\Psi(\mathbf{m}, r_A)\left(\alpha_i \frac{\partial x(m_i, r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j, r_A)}{\partial m}\right)$$

$$0 > \left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right)$$
$$\rightarrow \exists \varepsilon > 0 \text{ s.t. } [\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)] < 0 \; \forall \; \Delta \in (0, \varepsilon)$$

$$\left(\frac{\partial x(m_i, r_A)}{\partial m} - \frac{\partial x(m_j, r_A)}{\partial m}\right) > -\Psi(\mathbf{m}, r_A)\left(\alpha_i \frac{\partial x(m_i, r_A)}{\partial m} - \alpha_j \frac{\partial x(m_j, r_A)}{\partial m}\right)$$
$$\rightarrow \exists \gamma > 0 \text{ s.t. } [\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] > 0 \; \forall \; \Delta \in (0, \gamma)$$
$$\Rightarrow \text{sign}[\bar{x}(\mathbf{m_B}, r_B) - \bar{x}(\mathbf{m_A}, r_A)] \neq \text{sign}[\bar{x}(\mathbf{m_B}, r_A) - \bar{x}(\mathbf{m_A}, r_A)] \; \forall \Delta \in (0, \min\{\varepsilon, \gamma\})$$

C.3.6 Proof of Corollary 1

Take any $\mathbf{m_A} \in M^N \subset \mathbb{R}^N_+$. Let $\mathbf{m'_A}$ be the permutation of $\mathbf{m_A}$ which results in the highest (lowest) aggregate positional consumption among all such permutations, i.e. $\mathbf{m'_A} = P[\mathbf{m_A}]$ such that $\bar{x}(\mathbf{m'_A}, r'_A) \geq (\leq) \bar{x}(\mathbf{m^P_A}, r^P_A)\ \forall\ \mathbf{m^P_A} = P[\mathbf{m_A}]$. Let $\mathbf{m''_A}$ be another permutation of $\mathbf{m_A}$ such that $\bar{x}(\mathbf{m'_A}, r'_A) < (>) \bar{x}(\mathbf{m''_A}, r''_A)$. By definition, it holds that $\mathbf{m'_A} \succ_m \mathbf{m''_A}$ and $\mathbf{m''_A} \succ_m \mathbf{m'_A}$. We then apply to $\mathbf{m'_A}$ a small transfer Δ from j to i, where $m_i < (>) m_j$, to give $\mathbf{m_B}$ ($\mathbf{m_C}$). For a small enough Δ, we have $\mathbf{m_C} \succ_m \mathbf{m''_A} \succ_m \mathbf{m_B}$ but $\bar{x}(\mathbf{m_B}, r_B) > (<) \bar{x}(\mathbf{m''_A}, r''_A)$ and $\bar{x}(\mathbf{m_C}, r_C) > (<) \bar{x}(\mathbf{m''_A}, r''_A)$.

More broadly, since $\exists (i, j)$ s.t. $\alpha_i \neq \alpha_j$, $\bar{x}(\mathbf{m}, r = h(\mathbf{m}, r))$ is not symmetric and thus neither Schur-convex nor Schur-concave.