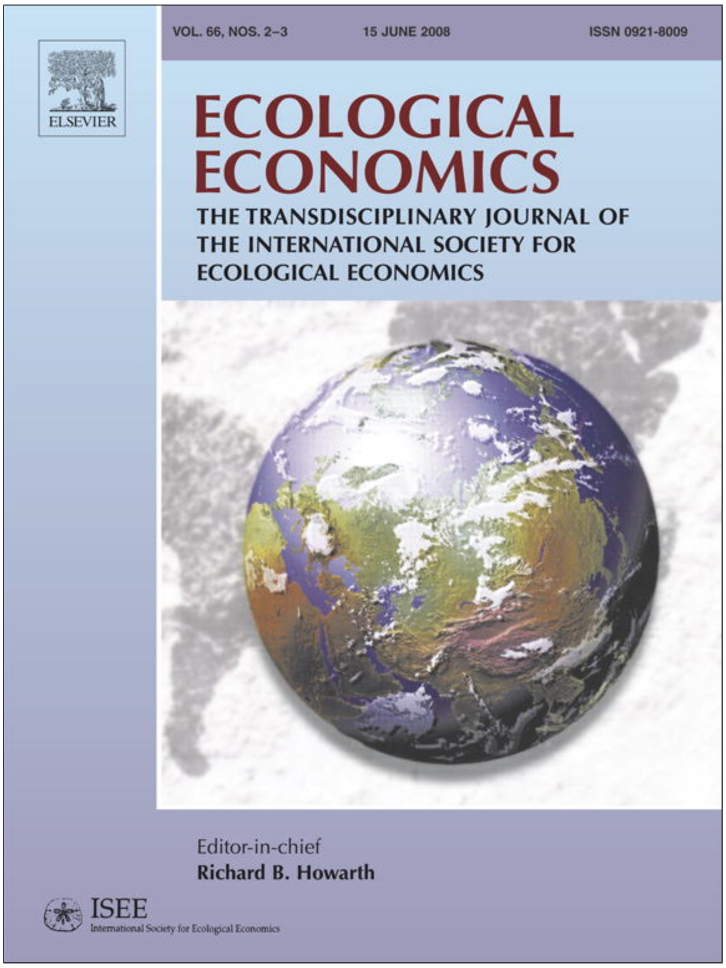
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ANALYSIS

Quantifying the global and distributional aspects of American household carbon footprint

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ABSTRACT

Analysis of household consumption and its environmental impact remains one of the most important topics in sustainability research. Nevertheless, much past and recent work has focused on domestic national averages, neglecting both the growing importance of international trade on household carbon footprint and the variation between households of different income levels and demographics. Using consumer expenditure surveys and multi-country life cycle assessment techniques, this paper analyzes the global and distributional aspects of American household carbon footprint. We find that due to recently increased international trade, 30% of total US household CO_2 impact in 2004 occurred outside the US. Further, households vary considerably in their CO_2 responsibilities: at least a factor of ten difference exists between low and high-impact households, with total household income and expenditure being the best predictors of both domestic and international portions of the total CO_2 impact. The global location of emissions, which cannot be calculated using standard input–output analysis, and the variation of household impacts with income, have important ramifications for polices designed to lower consumer impacts on climate change, such as carbon taxes. The effectiveness and fairness of such policies hinges on a proper understanding of how income distributions, rebound effects, and international trade affect them.

1. Introduction

Analyzing the energy and environmental emissions requirements of household consumption has been one of the most well-studied aspects of the environmental and life cycle assessment (LCA) literatures for many years (Bullard and Herendeen, 1975; Lenzen, 1998; Reinders et al., 2003; Tukker and Jansen, 2006). However, it remains of interest due to changing energy, emissions, and consumption patterns and increasingly refined and varied modeling techniques (Kok et al., 2006; Lenzen et al., 2004; Tukker and Jansen, 2006; Wier and Lenzen, 2001). At the same time, there has been increasing interest in studying the environmental effects of globalization and international trade at the national level (Lenzen et al., 2004; Peters and Hertwich, 2006; Streets et al., 2006; Wiedmann et al., 2007). As global trade increases, it becomes more important to include international differences in economic efficiency, production and process methods, and energy/emissions structures in environmental models, as neglecting these differences produces significant errors in national-level environmental analysis (Ahmad and Wyckoff, 2003; Peters and Hertwich, 2006). Much of this research has focused on the potential for 'carbon leakage' outside the regulatory control of the Kyoto protocol (Babiker et al., 2000; Babiker, 2005; Bin and

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Harriss, 2006; Kander and Lindmark, 2006; Maenpaa and Siikavirta, 2007), which presents serious problems to Kyoto signatories in the developed world.

Relatively little research has attempted to connect the household impact and international trade literatures to explore the global environmental impacts associated with household consumption of goods and services (Peters and Hertwich, 2006). This connection is important because current international efforts at controlling climate change focus at a national level, and one obvious way to lower national emissions is to displace carbon-intensive production (Bin and Harriss, 2006; Maenpaa and Siikavirta, 2007; Weber and Matthews, 2007b). Further, many studies of household energy requirements (HER) or environmental impact (HEI) have focused on 'average' households within a region or country and thus miss the tremendous variation in HER/HEI between households of different sizes, incomes, and expenditure patterns. Notable exceptions have, for the most part, focused on total energy requirements of household consumption as opposed to directly linking energy and household impacts (Lenzen, 1998; Lenzen et al., 2006; Vringer and Blok, 1995; Wier and Lenzen, 2001).

These omissions are due to some extent to complexity issues; for example, it is very difficult to model the global supply chains feeding household consumption with a high degree of certainty due to inadequate data in trade statistics and household consumption surveys. However, these uncertainties do not make this line of research insignificant or insurmountable. Such information may be useful for educational purposes in promoting more sustainable consumption patterns, and it is of vital importance to understanding both the effectiveness and the distributional impacts of national-level policy efforts toward climate change, such as the taxation of carbon dioxide or energy goods (Baranzini et al., 2000).

Here we build on previous analyses of HER and HEI to more clearly link consumption by different American household types to their global household carbon footprint (HCF), one important aspect of environmental impact. The United States is an ideal candidate for this analysis for several reasons. First, the US is home to the world's most influential consumer class. Second, consumer goods purchased in the US have become increasingly globalized as US trade has expanded rapidly in the past decades (Census, 2005; Weber and Matthews, 2007b). Third, data availability in the US is perhaps the best in the world for such an analysis; the input–output accounts, consumer expenditure surveys, trade data, and consumer price data are all very detailed (BEA, 2006; BEA, 2003; BLS, 2006a,b; Census, 2005). Finally, recent activity at the state and national levels shows the potential for future American action on climate change, and understanding the overall role of household consumption in US CO_2 emissions, the distribution of household responsibility, and how international trade shapes US HCF will be vital in designing appropriate and effective policies.

2. Methods and data sources

2.1. *Average HCF*

To analyze average HCF, we build a unidirectional industry-by-industry multiregional input–output (MRIO) model of the United States and its 7 largest trading partners, approximating US consumption and trade patterns for 2004 (see (Wiedmann et al., 2007) for a recent review of MRIO models). MRIO is a generalized form of input–output analysis (IOA) which yields an economic model of a country or region and its trading partners and allows for a detailed delineation of the entire supply chain of goods and services consumed in the country of interest, here the US. MRIO is especially useful for determining the location of various production factors (such as pollution, employment, energy, etc.) in the production of goods and services, which standard IOA cannot achieve. Derivation of the MRIO model has been described in previous work (Weber and Matthews, 2007b) and is shown in detail in Appendix A. Only the main aspects of the model are discussed here.

Eq. (1.1) shows the derived model, which calculates the total economic requirements, $\mathbf{x}$, (in \$US producer prices) in all countries to meet an input final demand, $\mathbf{y}$, in country 1. By solving for $\mathbf{x}$ and including an environmental matrix, $\mathbf{F}$, of energy or emissions per unit output (in \$US) in each industry and country, the total global supply chain emissions or energy can be calculated. Several assumptions made in the construction of the model are important: first, because only US consumption is of interest here, it was assumed that all exports from the US could be treated equally as final demand, regardless of their destination. Additionally, it was assumed that direct trade (a.k.a., first-level trade) dominates overall trade so that off-diagonal elements of the compound $\mathbf{A}$ matrix are assumed zero. The effect here is to limit the supply chain to the current country (group of countries) if 2 or more borders are crossed in the production of a good. It has been shown in previous work that in aggregate, the error this introduces may be lower than 1–2% (Lenzen et al., 2004). Of course, this error will vary depending on the commodity being modeled. For large groups of commodities such as the consumption baskets modeled here, explicit uncertainty analysis is impractical. Extensions to the model were made to internalize capital expenditures on machinery, software, etc. and to adjust from retail prices to producer prices, markups, and delivery. Details are found in Appendix A.

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_1^d & 0 & \cdots & 0 \\ A_{21} & A_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & 0 & \cdots & A_m \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_1^d + \sum_{j \neq 1} y_{1j} \\ y_{21} \\ \vdots \\ y_{m1} \end{pmatrix} \quad (1.1)$$

Even with these simplifications, the data requirements for this model remain large. In addition to the US economy, its top seven trading partners were included in the model: Canada, China, Mexico, Japan, Germany, the UK, and Korea. While the number of countries to include is somewhat arbitrary, seven were chosen for two reasons: first, after the top seven countries, the marginal increase in model coverage (as an economic percentage of total US trade) dropped below 3% (Census, 2005). Second, the top seven countries provided a good model set by which to approximate the remaining 'rest-of-world' (ROW) countries, which were mapped to one of the above countries using a cluster analysis method and several data from the 2005 Environmental Sustainability Index (Esty et al., 2005) and International Energy Agency (IEA, 2005). Table 1 displays the import shares of each of the countries individually, and the total import share of the group of countries assumed similar to the model country.

Table 1 – Model countries, year of IOT and number of original IOT sectors, US import share in $ terms before (Trade04) and after (Trade04map) inclusion of clustered rest-of-world (ROW) countries

	IOYear	Sectors	Trade04	Trade04map
Canada	1997	117	16%	19%
China	1997	124	15%	26%
Mexico	1989*	92	10%	20%
Japan	2000	104	9%	9%
Germany	2000	59	11%	9%
Korea	2000	168	3%	8%
United Kingdom	2000	49	3%	8%
United States	1997	491		1%
Total			100%	100%

*Environmental data from 1999.

For each country included in the model, three pieces of information were required: a production function (**A** matrix), import shares by industry, and environmental emissions by industry (**F** matrix). All IO data were taken from country statistical offices (BEA, 2002; Bjorn et al., 2005; Dimaranan, 2006; Director-General for Policy Planning, 2005; Eurostat, 2006; Bank of Korea, 2006). One significant problem with MRIO is year-to-year variation between different countries' input–output tables (IOTs) and the significant time-lag in their publication. For example, the most recent detailed benchmark IOT for the US (1997) is 10 years old. However, several studies have noted that changes in trade structure and emissions factors over time likely move much faster than changes in national production functions (see, for example, (Kander and Lindmark, 2006)). Since the aim of this analysis was to analyze the most recent structure of US trade and consumption, the year 2004 was chosen to conduct the analysis, which represented the most up-to-date trade and expenditure data. However, due to time-lag, this required two major adjustments to the data: price adjustments and import penetration adjustments.

Detailed gross output price indices (at a 490-sector level) were used to adjust from 2004 to 1997 producer prices (BEA, 2005a). It was implicitly assumed that the ratio of retail to wholesale prices did not change during this time period. Because the import matrix, $\mathbf{A}_m$, for 1997 does not accurately describe the use of imports for 2004 trade, alterations were made to the matrix using trade data and gross output data for these years (BEA, 2005b; Census, 2005). Relatively few countries track the use of imports by industry, and thus, import matrices are generally defined by assuming that each industry's use of commodity imports is proportional to the overall domestic supply of the commodity:

$$s_{ij} = \frac{m_j}{x_j - e_j + m_j} \tag{1.2}$$

where i and j denote an industry i's use of commodity j, **m** and **e** are total imports and exports of the commodity, and **x** is the total output of the commodity.

The supplementary import matrix supplied by the Bureau of Economic Analysis uses an 8000 commodity structure to derive $\mathbf{A}_m$, and thus, significant detail would be lost by simply recalculating the import matrix for 2002 and 2004 using the above approximation at the 491 sector level. Thus, the 1997 import matrix was altered using the ratio of the values of s_{ij} for 2004 divided by the value of s_{ij} for 1997:

$$a_{j2004} = s_{ij2004}/s_{ij1997} = \frac{\left(\frac{m_{j2004}}{x_{j2004}-e_{j2004}+m_{j2004}}\right)}{\left(\frac{m_{j1997}}{x_{j1997}-e_{j1997}+m_{j1997}}\right)} \tag{1.3}$$

This method allows an approximation of 2004 import penetration within the 1997 IO model while still maintaining the 1997 model's detailed structure.

CO_2 emissions data were taken from a variety of sources, including national sources (Statistiches Bundesamt, 2004; Environment Canada, 2004; Eastern Research Group, 2005; Harris, 2001), previous LCA projects in Japan and Canada (Nansai et al., 2002; Norman et al., 2007), and the International Energy Agency (IEA, 2005) where no better data could be acquired. Chinese data has been described in detail elsewhere (Peters et al., 2006b). For all countries, if data were not immediately available in the same sectoral format as the IOT, a concordance matrix was built between the IO sectors and the emissions data using sectoral descriptions from the IO databases. If multiple years of data were available, preference was given first to data from 1997 (the base year for the US IO data) then to the base year for the country's IOT, and finally to the most recent data. When data were not available for 1997, each country's consumer price index was used to convert to 1997. A more detailed method would utilize sector-specific price levels. Following conversion to 1997, yearly market exchange rates (MER) from the Penn World Table (Heston et al., 2006) were used to bring each country's environmental vectors into the common unit (tCO_2/\$1997USx10^6). While the alternative choice of using purchasing power parity (PPP) conversion rates has been suggested (Ahmad and Wyckoff, 2003; Peters and Hertwich, 2004), market exchange rates were used for this analysis with PPP values utilized for uncertainty analysis. A preliminary analysis using price levels between China and the US indicates that the 'true' exchange rate in 2004 was between the MER and PPP, but tended closer to the MER. Due to inhomogeneities in outputs, very few homogenous commodities (such as electricity, coal, etc) could be compared this way.

For the use phase portion of the model, purchases of energy goods (gasoline, diesel, fuel oil, and LPG) were converted from a dollar basis to physical units using seasonally and regionally-adjusted prices (EIA, 2006). Average emissions factors for direct consumer emissions in the use phase were derived and cross-checked from several sources, including (EPA, 1995, 2006; IEA, 2005).

2.2. *Distribution of HCF*

Data on consumer expenditures were taken from the 2004 Consumer Expenditure Survey (CES) of the Bureau of Labor Statistics (BLS, 2006a). This survey consists of a rolling sample of approximately 25000 households in the United States, 18000 of which are utilized for a quarterly interview survey on monthly expenditures and the rest used for a 2 week diary survey of smaller purchases, mostly food items. To obtain the most consistent sample possible, a total of 17250 households from the interview portion of the survey, each of which was in the survey for a different number of months, were utilized for the analysis. Each household's year 2004 purchases were totaled and averaged over the number of months the household took part in the survey, thus smoothing out purchases not made every month. Because only the diary portion included detailed home food purchases, households from the interview portion were matched with households from the diary portion for home food purchases only through a method similar to above for countries, where households were linked via minimizing Euclidean distance between the normalized variables of total home food expenditures, family size, and household income. While this assumed matching introduces a fair amount of uncertainty into the purchases of food at home, Figs. 1 and 2 show that less than 7% of total household expenditure and less than 7% of average HCF is attributed to food at home. Thus, the impacts on the overall analysis are likely small.

Approximately 300 distinct commodities are covered by the survey, which mapped reasonably well to the approximately 300 commodity sectors of the US economy in which households directly purchase output. Each of the two separate samples (the interview and the diary) were assigned socio-demographic weights by the BLS (interpreted as a total number of US households represented) according to their income and demographics, thus allowing extrapolation from the sample to the entire US population.

The treatment of durable goods in a cross-sectional analysis such as this is vital to correctly interpreting the distribution of HCF within the population. For instance, if one household purchases a television with an anticipated life of 10 years, while another purchased the same television last year, should the first be associated with more HCF simply due to timing? There are several ways to deal with this problem (see (Peters et al., 2006a) and (Aasness et al., 1993) for a detailed discussion of these issues), but perhaps the simplest is the approach taken here—to ignore all non-financed durable goods (i.e., automobiles and major appliances purchased outright). This can be justified on several grounds, including simplicity and transparency, but perhaps the best argument is that purchases of these goods, due to their longer life, tend to form a relatively small share of a household's environmental impact when compared to food, energy, mobility, and housing (Lenzen et al., 2006; Peters et al., 2006a; Tukker and Jansen, 2006). The life cycle environmental impact of these goods is generally dominated by the use phase, which is captured in energy purchases. It should be noted that consumer electronics represent an important exception to this rule (Weber et al., 2007; Williams, 2004). Housing requires special treatment; because housing costs are only tenuously related to environmental impacts of housing (Reinders et al., 2003), data on living space (number of rooms in dwelling) was utilized with total (capital included) impacts from the MRIO model to approximate the household-specific and time-averaged impacts of housing construction. Since housing constituted less than 5% of total HCF (see below), results were insensitive to the choice of dollar-based or living-space-based estimations of the impacts of housing.

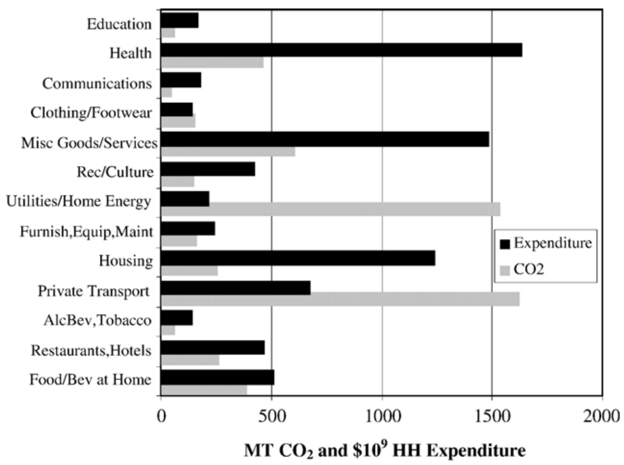

Fig. 1 – Total 2004 household expenditures ($\$10^9$, grey bar) and CO_2 emissions (Mt/yr) from household consumption, in 13 consumption categories.

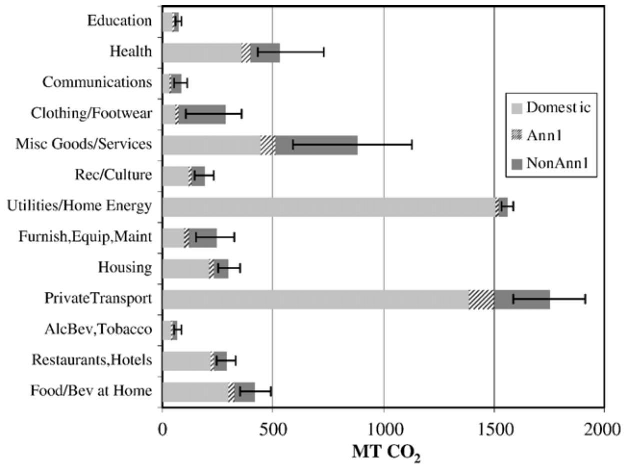

Fig. 2 – Total household CO_2 in 2004, by consumption category and location of emissions. Ann1 refers to ratified Annex 1 parties to the Kyoto Protocol and NonAnn1 refers to other countries. Uncertainty bounds are shown for the imported portion of the footprint, and represent a rest-of-world group modeled with German technology with PPP exchange rates (lower) and Chinese technology with MER exchange rates (upper).

In past work, expenditure and income have been found to be the strongest predictors of household energy requirements or environmental impacts (Bullard and Herendeen, 1975; Herendeen et al., 1981; Lenzen et al., 2006; Reinders et al., 2003). Here we test four common model forms to estimate the income and expenditure elasticities, ε, of HCF, defined as:

$$\varepsilon = \frac{\overline{y}}{\overline{CO_2}} \frac{\partial CO_2}{\partial y} \tag{1.4}$$

where y represents either yearly expenditure or yearly after-tax income. It should be noted that we use the concept of mean elasticities (Peters et al., 2006a), which differ from point elasticities in that they are calculated only at the mean values of expenditure/income and HCF, as opposed to over the entire expenditure or income range. This point is often ignored. Two of the models utilized here, (1) and (2), have point elasticities that are a function of income or expenditure, while models (3) and (4) possess the unique quality of having a constant point elasticity, possibly explaining their prevalence of use (Lenzen et al., 2006; Wier and Lenzen, 2001). All models control for household size using two variables, n_{child} and n_{adult}, the respective number of children and adults in the household. It is important to separate influences of these different types of household members, since they display very different consumption profiles (Peters et al., 2006a). The model forms and their associated mean elasticities are:

$$CO_2 = a + by + cn_{\text{child}} + dn_{\text{adult}}, \quad \varepsilon = \frac{\overline{y}}{CO_2} b \tag{1}$$

$$CO_2 = a + by + cy^2 + dn_{\text{child}} + en_{\text{adult}}, \quad \varepsilon = \frac{\overline{y}}{CO_2}(b + 2c\overline{y}) \tag{2}$$

$$CO_2 = ay^{\varepsilon}\exp(bn_{\text{child}} + cn_{\text{adult}}), \quad \varepsilon = \frac{\overline{y}}{CO_2}\varepsilon a y^{\varepsilon-1} = \varepsilon \tag{3}$$

$$CO_2 = ay^{\varepsilon} + bn_{\text{child}} + cn_{\text{adult}}, \quad \varepsilon = \frac{\overline{y}}{CO_2}\varepsilon a y^{\varepsilon-1} = \varepsilon \tag{4}$$

It should be noted that the only difference between models (3) and (4) is the way in which household size is controlled.

3. Results

3.1. Average HCF

While the focus of this discussion will be on international and distributional aspects of U.S. household carbon footprints, a short analysis of total (i.e., average) HCF is warranted for benchmarking purposes — several similar studies using single-region input–output analysis have been performed for households (see (Tukker and Jansen, 2006) for a recent review). We use total household final consumption data from the 2004 Annual US IOT for this calculation. Fig. 1 shows the main results for total household expenditures, in 2004$B, and resulting life cycle CO_2 emissions assuming that all production takes place domestically (the standard assumption in IOA, i.e., the 'domestic technology assumption'). The results are broken down into 13 commonly used broad consumption categories similar to those used in recent work (Tukker and Jansen, 2006). For the interested reader, CO_2 intensities of all CES commodities and their assigned consumption categories are posted online (Weber and Matthews, 2007a).

As would be expected, different consumption categories have very different shares of both expenditure and HCF. On the broadest scale, aggregate household consumption totaled $8100B in 2004 and resulted in 5700 Mt of CO_2, for an average CO_2 intensity of consumption of about 0.7 kg CO_2/$. Some consumption categories, such as education, health care, recreation and culture, and communications have intensities much lower than this while others, such as home energy and utilities and personal transportation, have much higher intensities. On average, each American household would have been responsible for 50 t CO_2 in 2004 if all production took place in the US. After correcting for trade (subtracting emissions embodied in imports and adding emissions embodied in exports) and adding governmental consumption, these overall numbers match reasonably well with EPA estimates of total production inventories (EPA, 2006). The absolute numbers agree reasonably well with recent studies of the US (Bin and Dowlatabadi, 2005), and categorical breakdowns are similar to this study and to studies of European countries with similar standards of living (Reinders et al., 2003; Tukker and Jansen, 2006), with the exception of much higher household expenditures and impacts of private health care in the US when compared to the EU. In previous EU studies, impacts due to health care may have appeared much lower due to it being accounted for in taxes and governmental expenditure as opposed to private expenditure (Tukker and Jansen, 2006). Of course, in absolute numbers the average American HCF is higher than most European countries due to higher levels of expenditure and a relatively high-carbon primary energy mix.

This 'average' HCF changes substantially when imports are modeled explicitly. Fig. 2 shows similar results as Fig. 1 but with imports modeled using the MRIO model. Total HCF is split up between emissions occurring domestically, emissions occurring in ratified Annex 1 parties to the Kyoto Protocol (most of the developed world) and non-Annex 1 parties (most of the developing world and Australia) (UNFCCC, 2006). It should be noted that the model integrates imports into US production and consumption to infinite order, so that imports of final products are seen in such categories as misc. goods and services, food, and clothing/footwear, and imports further down the supply chain are seen in all categories, such as the oil, raw materials, primary metals, etc. used in the manufacture of the goods and in the machinery and equipment used to make the goods.

The different consumption categories show vastly different global shares, ranging from the extremes of clothing and footwear, where nearly all products are produced abroad, to home energy and utilities, where direct domestic consumer emissions for heating and electricity emissions dominate overall emissions. Overall, because the imported share is produced using less efficient technology and higher emissions intensities, the best-guess total HCF goes up for all categories to a new total of 6700 Mt (57 t/household), with 4800 Mt occurring domestically, 400 Mt in Annex 1 Kyoto parties, and 1500 Mt in the developing world (42, 3, and 12 t CO_2/household, respectively). In short, 29% of CO_2 to meet household demand in the US occurs abroad and a 15% increase is seen when imports are modeled explicitly.

The uncertainty in estimating such emissions also increases as the imported share goes up, due to uncertainties in monetary exchange rates and in the concordance of non-modeled countries (rest-of-world, ROW) to the model countries. Previous work has shown that model output is very sensitive to the treatment of these ROW countries since the top 7 trading partners only account for approximately 60% of US trade (Weber and Matthews, 2007b). Thus, a bounding estimate is given in Fig. 2 by bounds representing an entirely German-modeled ROW and an entirely Chinese-modeled ROW. Because these two countries represent the most environmentally-efficient and least environmentally-efficient countries in the model, they represent a good first estimate of the uncertainty in the ROW treatment. The assumed currency exchange rates between countries have been shown to be another major uncertainty in the creation of MRIO models (Ahmad and Wyckoff, 2003; Peters and Hertwich, 2004), so the range shown in Fig. 2 incorporates this uncertainty as well by using purchasing power parity (PPP) values in the lower-bound and market exchange rates (MER) in the upper bound. While

Table 2 – Regression results for total HCF and domestic and foreign shares of HCF predicting expenditure (above) and income (below) for four model forms including significance level, 95% confidence interval, and R^2 value

HEI	Param\Model	(1)	(2)	(3)	(4)
Total	ε	0.60***(0.60–0.61)	0.68***(0.67–0.68)	0.68***(0.67–0.68)	0.7***(0.76–0.78)
Total	Child	1.75***(1.58–1.93)	1.63***(1.451.80)	1.04***(1.04–1.05)	1.62***(1.45–1.80)
Total	Adult	4.60***(4.35–4.85)	4.00***(3.7–54.25)	1.12***(1.11–1.13)	3.77***(3.52–4.02)
Total	R^2	0.71	0.72	0.71	0.72
Domestic	ε	0.53***(0.52–0.54)	0.62***(0.590.65)	0.64***(0.63–0.65)	0.72***(0.71–0.73)
Domestic	Child	1.53***(1.38–1.68)	1.41***(1.26–1.56)	1.05***(1.04–1.05)	1.41***(1.26–1.56)
Domestic	Adult	4.50***(4.20–4.72)	3.95***(3.74–4.17)	1.15***(1.14–1.16)	3.72***(3.51–3.94)
Domestic	R^2	0.64	0.65	0.64	0.65
Foreign	ε	0.89***(0.88–0.90)	0. 91***(0.86–0.97)	0.80***(0.79–0.81)	0.94***(0.92–0.96
Foreign	Child	0.21***(0.14–0.28)	0. 20***(0.1 4–0.27)	1.04***(1.03–1.04)	0.20***(0.1 4–0.27)
Foreign	Adult	0.13**(0.03–0.22)	0.09 (−0.01–0.18)	1.05***(1.04–1.06)	0.12**(0.02–0.21)
Foreign	R^2	0.56	0.56	0.54	0.56
Total	ε	0.35***(0.35–0.36)	0.47***(0.4&0.49)	0.36***(0.36–0.37)	0.52***(0.51–0.53)
Total	Child	3.00***(2.76–3.23)	2.79***(2.563.02)	1.09***(1.08–1.09)	2.76***(2.53–2.99)
Total	Adult	5.93***(5.59–6.26)	4.64***(4.30–4.98)	1.18***(1.17–1.19)	4.61***(4.27–4.95)
Total	R^2	0.48	0.51	0.49	0.51
Domestic	ε	O.32***(O.31–O.33)	0.43***(0.410.45)	0.36***(0.35–O.36)	0.49***(0.48–0.51)
Domestic	Child	2.38***(2.19–2.56)	2.22***(2.04–2.40)	1.09***(1.08–1.09)	2.19***(2.01–2.37)
Domestic	Adult	5.31***(5.04–5.57)	4.32***(4.054.59)	1.20***(1.19–1.21)	4.23***(3.96–4.49)
Domestic	R^2	0.46	0.49	0.48	0.49
Foreign	ε	0.49***(0.47–0.50)	0.62***(0.58–0.66)	0.41***(0.40–0.42)	0.61***(0.59–0.63)
Foreign	Child	0.61***(0.52–0.69)	0.56***(0.47–0.64)	1.09***(1.08–1.14)	0.56***(0.47–0.64)
Foreign	Adult	0.64***(0.52–0.77)	0.34***(0.22–0.47)	1.13***(1.08–1.14)	0.42***(0.30–0.55)
Foreign	R^2	0.31	0.33	0.29	0.32

the difference between these exchange rates is small between countries of similar development stage, when comparing interactions in developed-developing world trade, such as between the US and China or Mexico, the difference is larger. The PPP rate makes the developing world look more environmentally efficient (Peters and Hertwich, 2006; Weber and Matthews, 2007b), thus justifying the use of PPP for lower-bounds and MER for upper-bounds on uncertainty. Accounting for this uncertainty, the expected ranges on average household CO_2 are 48–67 t CO_2/yr (13–37% abroad). It is encouraging that using such vastly different models the range of household impact is still within +15–20% of the base case.

3.2. *Distribution of HCF*

Regression results for prediction of total HCF, as well as domestic and foreign portions of HCF, for each of the four models are shown in Table 2 for expenditure (top) and income (bottom). Fig. 3 shows a visualization of the total HCF data for the CES households, along with the marginal model fits (i.e., without controlling for household size for visualization purposes) for models (1), (2), and (4). (Model (3) is equivalent to model (4) without controlling for household size.) Prior to running the regression, outliers were removed using a studentized residual of >3 rule, which removed less than 200 of the 17000 data. As has been reported elsewhere (Herendeen et al., 1981; Reinders et al., 2003; Wier and Lenzen, 2001), expenditure explains more variation than income, which is expected due to the assumed Leontief-style model form connecting HCF to expenditure through economic structure. Similarly, as shown in previous work, the data show a heteroskedastic structure with expenditure, reflecting more diversity in consumption habits with higher overall expenditure. Even after outlier removal, there remains a large degree of scatter around the best fit lines, especially at high levels of expenditure. This result is promising for potential policy efforts toward promoting more sustainable consumption patterns, since it shows that very different household impacts can occur for similar levels of household expenditure.

Clearly the results shown here are sensitive to model choice. While each of the four models showed similar R^2 values (the values shown are adjusted R^2 values, all calculated for the untransformed HCF independent variable), total HCF

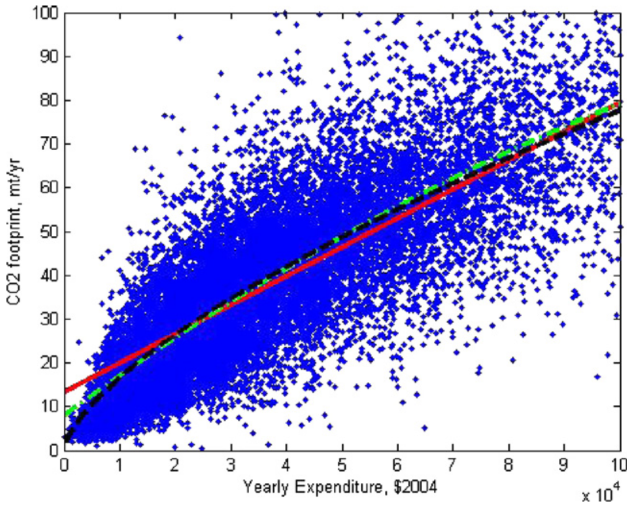

Fig. 3 – Scatter plot of CO_2 footprint by total household expenditure with 3 model fits — (1), red solid line, (2), green dashed line, and (4), black dashed line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

elasticities vary from 0.6 to 0.8 for expenditure and from 0.35 to 0.52 for income. These values are in general similar to reviewed results cited by Lenzen et al. (2006) and Reinders et al. (2003) for total energy requirements in several countries. It should be noted that the quadratic model (2) and the log–log model form (models (3) and (4)) generally performed best and agreed with each other to some degree, but the way in which household size is controlled for in the log–log relationship confounded the results, due in part to both model form and to multicollinearity between expenditure/income and household size (Spearman's correlation coefficient ρ=0.20 for expenditure–child and ρ=0.36 for expenditure-adult). As seen in Fig. 3, the model forms are very similar except for very small or very large expenditures. Previous authors have suggested one model form or another for various reasons, from theoretical economic foundations (Peters et al., 2006a) to empirical reasons (Lenzen et al., 2006), and the results show that model choice does matter significantly.

While all studies previously seen by the authors have reported results for total energy requirements(Lenzen et al., 2006; Reinders et al., 2003; Vringer and Blok, 1995), the MRIO model incorporated here allows a breakdown of HCF into domestic and international shares, which provide additional insight: both display similar form to the total HCF, although R^2 values are much higher for the domestic portion than the international portion. This may be because although all purchases will have at least some portion of their supply chain impact domestically (i.e., delivery and retailing), the international portion of HCF will be much more dependent on the detailed breakdown of commodities purchased and their import ratios. Thus, a more detailed look at how categorical consumption varies across expenditure and family size is warranted.

Fig. 4 show this distribution of categorical HCF by regressing each household's categorical consumption shares against total annual expenditure (left) and averaging categorical consumption shares over household size (right). Several interesting trends can be noted. The first is the overall shape of the relationship — HCF and expenditure form a nearly, but less-than, linear relationship, and as previously noted, household size shows increased eco-efficiency with increases in household size. In other words, per-capita CO_2 requirements decline with household size. The pattern is especially apparent beyond a household size of 3, where increases in household size have no statistically significant (α=0.05) increase in household CO_2 requirements on average, but do represent a significant shift between consumption categories — home size, home energy use, and food all increase on average past this point, but are mitigated by decreases in other categories such as misc. goods and services, communications, restaurants and hotels, and household furnishings. Transportation impacts are nearly constant beyond a family size of 3.

Also interesting is the mix of consumption categories as a function of expenditure (similar results are seen for income). It is clear from Fig. 4 that lower income and expenditure groups tend to generate a larger share of their CO_2 burden from what could be referred to as 'necessities'—food, housing, utilities, and personal transportation. While the HCF from these categories grows with increased expenditure, there is a diminishing returns effect, and the share of HCF associated with these categories drops continually as other consumption categories become more important: household furnishings and equipment, clothing and footwear, and most prominently miscellaneous goods and services, which includes electronics, toiletries, personal care, day care, and other services. It is important to note that the most CO_2 intensive categories (transport, home energy, and food) are precisely the items which make up the bulk of low-income consumption bundle. Thus, as income increases, households are able to choose either more of the high-carbon categories, (e.g., bigger houses or cars, increased air transport) or to shift more income to previously unaffordable lower-HCF categories such as increased communications, leisure goods, more education, or better health care. Because of this, the distribution of HCF around the mean prediction should increase with income and expenditure, which it does, as seen in Fig. 3.

An interesting side effect of these results is that because the international portion of the total supply chain is lower for most of the 'necessity' categories than for many of the

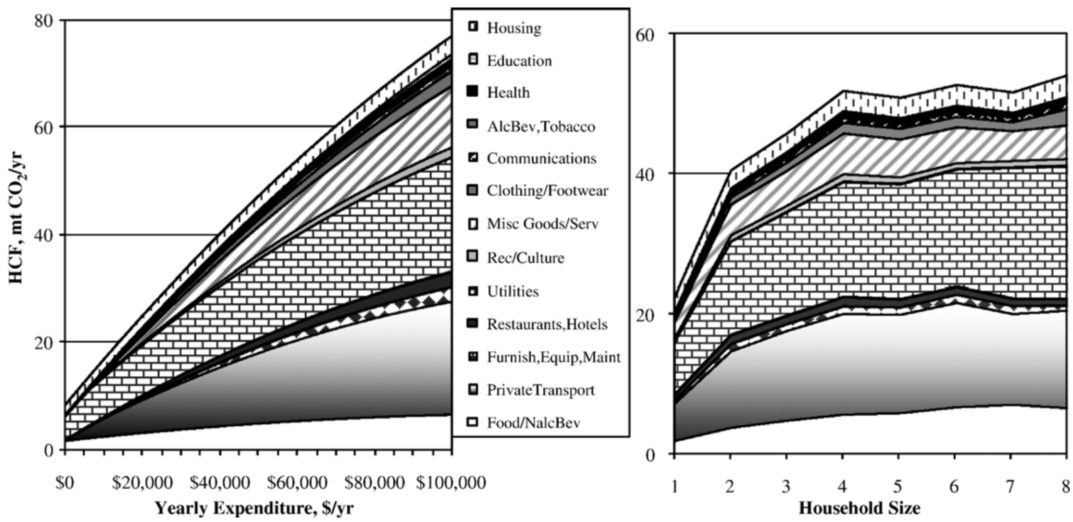

Fig. 4 – Regression results for different consumption categories' CO_2 plotted against expenditure (left) and total household size (right). Categories are listed in legend in order they appear on plot.

categories associated with higher consumption levels, Fig. 2, the international portion of HCF tends to rise with income on average. However, this varies significantly by household, as the international portion of HCF is a function of the detailed breakdown of commodities in the household's consumption bundle. Nevertheless, this effect could have policy-relevant impacts, as discussed below.

Several other demographic predictors can be added to such a model to increase predictive power and/or interpretability. Common variables include urbanity, dwelling size, education level, and so on (Lenzen et al., 2006). However, when this is done, a rigorous treatment of multicollinearity is necessary, as nearly any demographic variable is correlated with income and expenditure. Preliminary analysis showed that adding additional demographic detail does not add much to the explanatory power of the model, but does add collinearity problems. Regression analysis may not be the best framework for such comparisons; cross-sectional correlation analysis and cluster analysis are more likely to be insightful. Both are under investigation by the authors but are outside the scope of the current analysis.

4. Discussion

4.1. *Reliability of results*

Input–output analysis, the primary analysis method utilized in this paper, has several types of uncertainties associated with it, including aggregation, time-lag, and the assumption of domestic production of imports. Due to lack of data on the size of uncertainties within IOTs, detailed uncertainty analysis is uncommon, though some authors have provided a detailed theoretical discussion of IOA uncertainties (Lenzen, 2000). The use of MRIO, while solving the domestic production assumption in theory, in practice adds several other uncertainties, as discussed above. However, it is vital for understanding the domestic/international dynamics of HCF in a globalizing world. For a detailed discussion of uncertainties in IOA and MRIO, see (Lenzen, 2000; Lenzen et al., 2004).

Even less discussed in past literature have been the uncertainties inherent in using consumption surveys combined with IOA. While they allow distributional analysis, CES possess several potential issues for analysis of HCF. One obvious problem is that no survey could accurately take in every commodity purchased by households. Little of the past literature on combining CES and household impacts (Bullard and Herendeen, 1975; Reinders et al., 2003; Vringer and Blok, 1995; Wier and Lenzen, 2001) has formally attempted to analyze how much of the total requirements or impacts could even theoretically be captured in a consumption survey, though work in the Netherlands (Wilting, 1996; Kok et al., 2006) has considered this question in some detail. Table 3 explores this question for the U.S. in 2004 by comparing the total expenditure and HCF from the CES, weighted to the total population of US households (BLS, 2006a), to the total macro-scale expenditure and HCF taken from the personal consumption expenditures portion of the US IOT (similar to the calculation of Average HCF above). The percent of total HCF captured by the CES varies widely, both in expenditure and CO_2, from a low of 8% capture in health expenditures to a high of 125% in food and nonalcoholic beverages, which is likely due to the uncertainty of matching the diary households with interview households for this category.

Particularly poorly captured categories, where the weighted CES considerably underestimates the IO total, include health care, clothing and footwear, alcoholic beverages and tobacco, and household furnishings and maintenance. These categories may have been underestimated for several reasons: sampling bias (households spending time and money on health care may self-select out of a voluntary survey due to illness), cognitive biases (respondents underestimating their actual purchases on goods perceived as undesirable, such as alcohol/tobacco), errors in weighting from sample to population, and/or deliberate exclusion of some durable goods, like household appliances. On the whole, 62% of the total IO expenditure for the country and 70% of the total HCF from the IO data were captured in the weighted CES. Although these totals are not entirely encouraging, Table 3 does suggest that most of the high-HCF categories are captured reasonably well (utilities, housing, and to a lesser degree transport) and that besides the diary-extrapolated food category, categories were at least uniformly under-estimated, and thus are unlikely to be comparatively biased.

Table 3 – Comparison of total expenditure (0^9) and total CO_2 (Mt) captured by CES using demographic weights

Category	CO_2 CES, Mt	CO_2, IO, Mt	Exp, CES, 10^9	Exp, IO, 10^9	% CO_2	% Expend
Food/SevatHome	524	419	685	514	125	133
Restaurants,Hotels	126	269	222	472	44	47
AlcBev, Tobacco	23	67	52	144	34	36
PrivateTransport	1264	1756	361	678	72	53
Housing	296	296	1241	1241	100	100
FurnishEguipMaint	105	246	139	247	42	56
Utilities/Home Energy	1497	1561	211	219	96	96
Rec/Culture	92	192	199	425	46	47
MiscGoods/Services	499	666	1117	1488	56	15
Clothing/Footwear	120	266	72	143	42	50
Communications	65	65	117	181	76	65
Health	40	533	169	1638	8	10
Education	38	72	85	169	52	50
Total	4693	6694	4669	7557	70%	62%

% columns show what percentage of total expenditure or CO_2 from the IOT is captured by the weighted CES.

These results stand in contrast to those of Kok et al., who found that for the Netherlands in 1996, total capture of expenditure was around 86% and energy was around 92% (Kok et al., 2006). At least part of this difference is due to the highly-underestimated category Health Care (disregarding health care, capture rises to 76% for both expenditure and CO_2), which is publicly provided in the Netherlands and thus outside of household expenditures. Some of the other poorly-estimated categories in this work, such as household furnishings and maintenance were also poorly captured in (Kok et al., 2006) but not all; clothing compared well between methods in this work. More examples of such comparisons are needed in the literature to further elucidate the reasons for these differences.

Several other CES-specific uncertainties are likely important, such as recall/self-report error, price/quality issues, and time-averaging of purchases between income groups. Recall error occurs when respondents incorrectly report actual expenditures during the electronic interview at month's end. A preliminary analysis using the same data set but only including households who used check or bank stubs a significant portion of the time revealed similar results as in Table 2, suggesting that even if recall error is significant at a micro-household scale, in aggregate over and underestimation may cancel each other out. Price issues are also extremely important, as the IO-CES framework assumes that all households purchase similar priced items within the aggregate commodity groups. This is clearly not true, and leads to an overestimation of elasticities if higher-expenditure households purchase higher-priced goods. However, without more detailed data on physical units consumed, determining this effect's size is impossible for this study. Work in the Netherlands (Vringer, 2005) with physical unit data in a consumption survey led to a reduction of the energy elasticity of expenditure from 0.63 to 0.56–0.60.

Finally, the length of time households spend in the survey may be important for reasons listed above in the discussion on durable goods — households in the survey for only 1 month of the year are potentially more likely to experience out-of-the-ordinary consumption patterns than households in the survey for all 12 months of the year. This is another issue often ignored in such analyses, probably due to data limitations; most countries use a diary survey where each household notes their purchases for less than 1 month (Peters et al., 2006a). To some degree this can be controlled by deleting outlier households with extremely large expenditures in one category or by using robust fitting techniques which down-weight large residuals. Both methods were utilized here, and neither alternative outlier specifications (studentized residuals, Cook's D statistic) nor bisquare weighting robust fitting altered the calculated elasticities by more than 10%, probably due to the very large sample size (~17000).

However, since the US surveys utilize monthly interview surveys, a comparison is possible between households in the survey for different numbers of months. Since each grouping of households (i.e., the households in the survey for 1 month, 2 months, etc.) had a different number of households, ranging from 1,960 households in the survey for 6 months to only 485 in the survey for all 12 months, the data had to be normalized to the same sample size to be comparable. A bootstrap simulation (n=1000 iterations) was conducted where 450 randomly selected households from each survey length grouping were used to regress total HCF with expenditure using models (2) and (4). The mean results (mean elasticities and mean R^2 values) from the simulation are shown in Fig. 5. While there is no clear pattern in the simulated elasticities, it is clear that the R^2 value does increase with time spent in the survey, indicating that variation in month-to-month spending is a major uncertainty in the calculation of HCF elasticities. There is a clear jump in just averaging over 2 months of spending as opposed to one; the mean R^2 jumps by nearly 0.10, which partially throws into question analyses done with very short-term diary data. It also seems that a further increase is found by increasing the time in survey from 9 to 12 months, which may be associated with variation in energy use in colder months at the beginning and ending of the year.

4.2. Relevance of results

Given the desire to decrease the CO_2 emissions associated with household consumption, several options are available: improving production efficiency of the goods purchased, decreasing overall consumption volume, or changing the structure of consumption towards a more sustainable bundle of goods and services (Kander and Lindmark, 2006; Lenzen, 1998; Suh, 2006; Wier and Lenzen, 2001). Given the political unattractiveness of reducing aggregate consumption, most policy and research effort has focused on increasing CO_2 efficiency in production methods and realigning consumer preferences toward less CO_2-intense goods and services (Hertwich, 2005). The wide variation seen in Fig. 3 inspires hope that realigning preferences could have an effect, as all levels of expenditure have households with a significantly lower CO_2 impact than their expenditure would predict.

We find similar overall elasticities of expenditure and income as several previous studies (0.7–0.9 for expenditure, 0.4–0.6 for income, see (Peters et al., 2006a) for a review of previous results), further showing the broad agreement of decreasing marginal household impact with increased expenditure and income(Herendeen et al., 1981; Lenzen et al., 2006; Vringer and Blok, 1995; Wier and Lenzen, 2001). However, we also show that the calculated value of elasticities is sensitive to

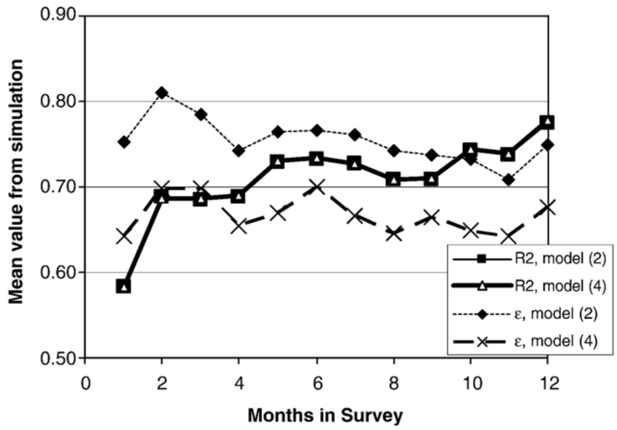

Fig. 5 – Mean R^2 values and 95th percentiles from bootstrap simulation of randomly selected households in the survey for the same number of months.

model choice, probably due to multicollinearity, which potentially explains some of the variation in calculated elasticities in past literature. Further, the novel use of MRIO in this study clearly allows additional information on the location of impacts due to households, showing in general that impacts from goods produced outside the US increase much faster with additional expenditure and income than domestic impacts.

The location of CO_2 emissions to meet household demand are important for the imposition of policies designed to realign consumer preferences, since most of these policies, such as carbon taxes(Baranzini et al., 2000), would take place at the national scale, at least at first. This work shows that nearly 30% of CO_2 emitted to meet household demand in the US occurs outside the country's borders, and this percentage varies substantially between different commodity groups and households(Weber and Matthews, 2007a). Thus, if no additional effort is made to also control imports, such as carbon border tax adjustments, a significant portion of the US's total household impact would be undercounted. These concerns can be even greater in less carbon-intensive economies(Peters and Hertwich, 2006).

5. Conclusions

This paper shows that including global and distributional aspects in the estimation of HCF leads to important implications which are missed in studies focusing on national averages. We estimate that for the US in 2004, when global differences in production structure and emissions intensities are taken into account, the average CO_2 to meet household consumption increases by 15% and in total, around 30% of US household CO_2 impact occurs outside of the US. When income distribution and differences in consumption structure are included, it is clear that households vary considerably in their responsibility for carbon emissions. Given these facts, policies designed to change household consumption patterns must consider both distributional aspects and international trade to be effective.

Acknowledgements

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Appendix A. Detailed methodology derivation

Appendix A.1. MRIO model development

Input–output analysis (IOA) has seen growing use in the field of life cycle assessment recently (Tukker and Jansen, 2006), but its origins date back to Leontief's original formulations in the 1930's and further development in the 1950's–1960's (Leontief, 1970). IOA has several advantages for use in environmental assessment, such as being able to easily delineate the entire economic supply chain of any good or service included in a country's IOT. However, IOA has its drawbacks, as most published IOTs are at the national level, and modeling usually assumes domestic production of imports, which can lead to significant modeling errors in open economies. IOA's lack of specificity (i.e. aggregation) is also significant, but for large groups of products, these errors tend to cancel (Lenzen, 2000) and the alternative, detailed process models, involve an impractical amount of work. The use of MRIO theoretically solves the first major type of error in IO modeling by explicitly modeling different production functions for different regions of production (ie, countries). The use of more disaggregated IOTs, such as the 491×491 benchmark input–output model of the US (BEA) helps to minimize aggregation errors.

As originally formalized by Leontief in his groundbreaking work (Leontief, 1970), the total output of an economy can be expressed as the sum of intermediate consumption and final consumption

$$x = Ax + y \tag{A1}$$

where A is the economy's production function in matrix form. When solved for total output, this equation yields:

$$x = (I - A)^{-1} y \tag{A2}$$

The production function for the economy can be generalized for an open economy, where exports are treated as a final demand, to (Miller and Blair, 1985; Peters and Hertwich, 2004):

$$x = \left(A^d + A^m\right)x + y^d + y^m + y^{ex} - m \tag{A3}$$

where A^d is the domestic portion of the production function (domestic interindustry demand on domestic goods), A^m shows domestic use of imports to make domestic products, and y^d, y^m, and y^{ex} represent final demands on domestic production, imports, and exports, and m represents total imports.

This idea can be generalized further to the m-region multiregional case, where each of m countries imports from every other country, to both interindustry demand as well as final demand. Here subscripts will denote region, and country in specific:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_1^d & A_{12} & \cdots & A_{1m} \\ A_{21} & A_2^d & \cdots & A_{2m} \\ \vdots & \vdots & \ddots & A_{2m} \\ A_{m1} & A_{m2} & \cdots & A_m^d \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_1^d + \sum_{j \neq 1} y_{1j} \\ y_{21} \\ \vdots \\ y_{m1} \end{pmatrix} \tag{A4}$$

Which shows the relation between total production in each country, x_j, and final demand in a single country 1. Each y_{j1} represents imports from country j to final demand in country 1 and y_{1j} represents country 1's exports to final demand in all other countries (Peters and Hertwich, 2004). As the data requirements for this general case are immense, usually a series of simplifications, depending on model usage, are appropriate.

If consumption only in country 1 (here the US) is important to the modeler, it can be assumed that all exports from country 1 can be treated equally as final demand. This simply states that where country 1′s exports go to are not of interest; it only matters that production, and thus emissions, occur in country 1 to make country 1′s exports. Additionally, to limit data requirements further, it can be assumed that direct trade (aka first-level trade) dominates overall trade so that off-diagonal elements of the compound **A** matrix are assumed zero. The effect is to redirect the remainder the supply chain to the current trading partner if 2 or more borders are crossed in a good's production. It has been shown in previous work that the error this introduces may be lower than 1–2% (Lenzen et al., 2004).

A choice can now be made between two different types of errors. One could use the domestic part of the country's production function, A^d, and accept the associated cut-off error. Alternatively, one could assume that the entire supply chain of the good in question occurs within the foreign country from which it was directly imported from, and thus use the entire production function, **A**. This includes the entire supply chain of the good but introduces regional mismatch error. Since A^d must usually be derived from approximation and trade shares, this choice also avoids the associated errors in the derivation of A^d from **A**. For this study, this was the approach taken.

After these assumptions are made, the final model can be derived as:

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} A_1^d & 0 & \cdots & 0 \\ A_{21} & A_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & 0 & \cdots & A_m \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix} + \begin{pmatrix} y_1^d + \sum_{j \neq 1} y_{1j} \\ y_{21} \\ \vdots \\ y_{m1} \end{pmatrix} \quad \text{(A5)}$$

After solving for the total output $\mathbf{x}=(x_1, x_2, \ldots x_m)^T$, it can be multiplied by the region-specific pollution matrix **F**, where $\dim(\mathbf{F})=(n \times m)$ and n is the number of pollutants of concern. Since all the domestic production functions are derived in terms of ratios, the units of the model output will be the same as model input, usually the currency of country 1. ($US1997 producer prices here)

This model expresses, then, the total economic requirements, **x**, (in $US producer prices) in all countries to meet total final demand, **y**, in country 1. By solving for **x** and including an environmental matrix, **F**, of energy or emissions per unit output (in $US) in each industry in the model, the total supply chain emissions or energy can be calculated. As is, the model only includes the total supply chain from raw material acquisition to factory gate; it ignores transportation to retail and emissions associated with wholesale and retail trade. The model may be extended further to include this extended supply chain by converting the retail price paid by the consumer into wholesale price, transportation, and retail/wholesale markups, using a matrix **T**. For arbitrary final demands (as opposed to total household final demand) it can be assumed that import ratios follow a similar pattern to overall demand, so that $1 spent in the US can be translated into shares spent on goods in each country/region using import shares in a matrix **M**. While this is not appropriate for a single purchase (a banana cannot be split into the halves produced in Costa Rica and Ecuador) it is appropriate for a series of purchases over a course of time. Finally, the inclusion of capital purchases, such as construction of factories to make goods, may be internalized into the model through the use of a capital flow matrix, **K**, which is also supplied by the BEA (BEA, 2003). Thus, the final form of the model, which derives the total global supply chain environmental impacts for a purchase in country 1 can be expressed as:

$$\mathrm{EI} = F(I - (A + K))^{-1}(MTy) \quad \text{(A6)}$$

Appendix A.2. Derivation of A_1^d, A_{m1}, K_d, K_m

For all countries besides the US, input–output tables were already in square industry-by-industry format ($l \times l$, were l is the number of industries in a given country). No alteration was thus necessary for foreign countries besides the aggregation from the original l sectors to the standardized 46-sector structure.

For the US, alterations were needed both to split the IOT into domestic and import portions and to aggregate the import portion to match the foreign IO data. The starting basis was the benchmark input–output files for 1997 in producer prices (BEA, 2002). For 1997, these tables show purchases and production of 483 commodities by 491 industries in the US economy. As detailed in (Peters and Hertwich, 2004) and (Miller and Blair, 1985), the domestic and import production functions (A_{1d} and A_{1m}) can be derived using the use matrix ($\mathbf{U_d}$, a commodity-by-industry matrix), the make matrix (**M**, an industry-by-commodity matrix), and the import matrix ($\mathbf{U_m}$, a commodity-by-industry matrix) as:

$$\begin{aligned} A^d &= DB^d = \left(M'\hat{q}^{-1}\right)\left(U^d\hat{g}^{-1}\right) \\ A^m &= DB^m = \left(M'\hat{q}^{-1}\right)\left(U^m\hat{g}^{-1}\right) \end{aligned} \quad \text{(A7)}$$

Where **q** is the total commodity output by the economy and **g** is the total industrial output and $\mathbf{A^d}$ and $\mathbf{A^m}$ represent the domestic and imported production functions for the economy.

This derivation is complicated somewhat by the use of a hybrid sectoral structure (where k is the number of desired sectors in economy 1, l is the desired number of sectors for economies $\neq$1, and $k \neq l$). This structure is utilized in order to keep the high level of disaggregation in the US IOTs in tact. If the desired dimensions are $k \times l$, Eq. (A7) can be modified slightly by S, the concordance or aggregation matrix, which matches the k sectors in economy 1 to the l sectors in the foreign economies:

$$\begin{aligned} A^d &= DB^d = \left(SM'\hat{q}^{-1}\right)\left(U^d\hat{g}^{-1}\right) \\ A^m &= DB^m = \left(SM'\hat{q}^{-1}\right)\left(U^m\hat{g}^{-1}\right) \end{aligned} \quad \text{(A8)}$$

To use this $\mathbf{A_m}$ matrix to derive $\mathbf{A_{21}}$ through $\mathbf{A_{m1}}$, a similar approximation is used as in (Lenzen et al., 2004) and (Peters and Hertwich, 2006): if each region's share of imports for a given sector is defined as $\mathbf{s_i}$, creating a vector of import shares **s** for each region or country, the approximation

$$A_{2m} \cong \hat{s}_m A^m \quad \text{(A9)}$$

can be used with relatively minimal error.

A similar process to above was followed for the domestic and imported portions of the capital flow matrix, **K**, which was taken from BEA supplemental estimates to the 1997 IOTs (BEA, 2003). Each capital commodity's import shares were assumed to be similar to the same commodity in the non-capital import matrix.

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