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Estimating Uncertainty in Household Energy Footprints

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Summary

We develop a methodology to characterize and quantify uncertainty in relating consumption to production in household energy footprints. This uncertainty arises primarily from inconsistencies between national accounts and household surveys and, to a smaller extent, from using aggregated sectors. Researchers may introduce significant inaccuracies by ignoring these inconsistencies when reporting household footprints. We apply the methodology to India and Brazil, where we find the size of this uncertainty to be higher than 20% of footprints at most income levels. We expect that previous estimates for these countries may have been overestimated due to these inconsistencies. Other knowledge gaps, such as inaccuracies in multiregional input-output tables and household surveys, add further uncertainty beyond our estimates.

Introduction

Household consumption is responsible for over 60% of global greenhouse gas (GHG) emissions (Ivanova et al. 2016). High heterogeneity in consumption patterns within and across countries makes it important, but difficult, to project growth in energy demand and GHG emissions based on a good understanding of these patterns. Underlying this challenge lurks a neglected source of uncertainty—the relationship between household consumption expenditure and national accounts of industrial production.

Researchers typically use input-output (IO) analysis to assess the energy and environmental impacts of household consumption (chapters 9 and 10, Miller and Blair [2009]). A common approach is to obtain from I-O models energy intensity estimates by industrial sector, which are then mapped to household consumption expenditures to yield energy footprints. In a globalized world, households in developing countries increasingly consume imported goods (Peters et al. 2011; Ivanova et al. 2016). With the growing use of global multiregional I-O (MRIO), a comprehensive analysis of household consumption has become feasible. This analysis is performed through a process visualized in figure 1.

Uncertainties in Estimating Household Footprints Using Multiregional Input-Output

Several sources of uncertainties arise in estimating household energy footprints, due to the use of diverse sources of data. There are uncertainties in the first place in compiling household surveys resulting from faulty sampling, recall bias, changes in survey design, poor supervision, or nonresponses (Deaton 2005). However, these are outside the control of applied research and not typically quantified.

The next challenge is to bridge country-specific household surveys to MRIOs, which have developed standardized, and typically aggregated, sectoral representation. While the use of aggregated (and fewer) sectors simplifies the task of mapping consumption to production sectors, it can bias energy footprint calculations, to the extent that the aggregated sectors' energy

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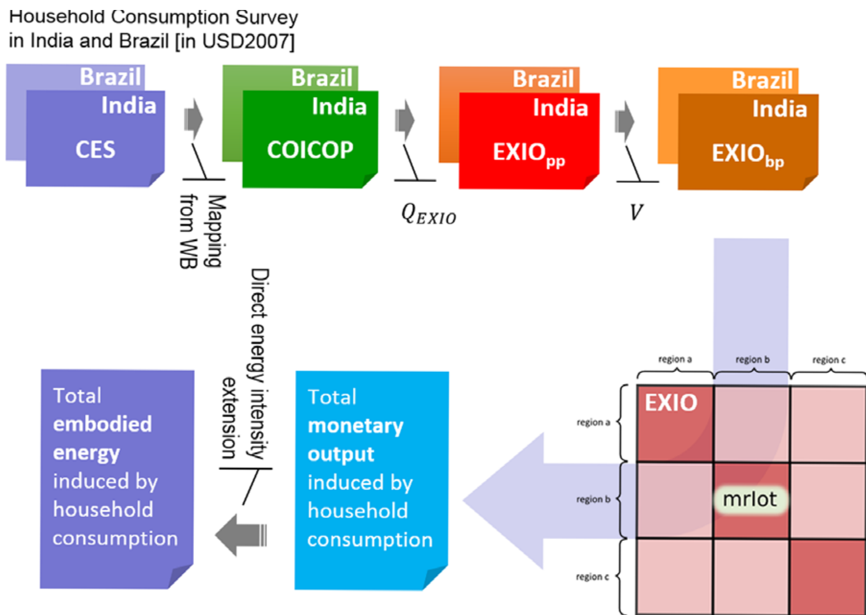

Figure 1 Overview of the classification mappings in this analysis. Small rectangles on the upper half represent household expenditure vectors (by consumption category) in different classifications and valuations. The lower half of the diagram follows the standard environmental I-O analysis process. CES = consumer expenditure surveys; COICOP = Classification of Individual Consumption According to Purpose; I-O = input-output; USD = U.S. dollars; WB = World Bank.

intensities and relative expenditure shares differ. In addition, household expenditure data from national surveys frequently differ from household final demand provided by I-O models in terms of both total and relative shares among items/sectors. Lenzen and colleagues (2014) suggest a platform to tackle this discrepancy in the construction of MRIOs.

Previous studies do not pay attention to the data uncertainties in this link. Indeed, most studies we found offer no detail on their assumptions underlying the bridge between household consumption categories and I-O sectors. Studies that estimate household consumption-based footprints use mostly single-region I-O models (Lenzen 1998; Pachauri and Spreng 2002; Lenzen et al. 2004a; Cohen et al. 2005; Lenzen et al. 2006; Park and Heo 2007; Liu et al. 2009; Minx et al. 2013) with a few exceptions that use global or subnational MRIOs (Lenzen and Peters 2010; Steen-Olsen 2015; Ivanova et al. 2016). Some of these works link consumer expenditure surveys to I-O models, as we do, to relate the footprints to other household level characteristics (Cohen et al. 2005; Lenzen et al. 2006, 2004a; Minx et al. 2013; Steen-Olsen 2015). Many of these studies do not disclose how they map surveys to I-O tables (IOTs). Those that do use deterministic mappings mainly based on researchers' judgments, in some cases using simple one-to-one mappings (Kok et al. 2006), which is more feasible when I-O models with higher levels of sectoral aggregation are used.

After bridging surveys to MRIOs, embodied energy intensities by household consumption category are derived from the MRIO model and its energy extension satellite (bottom half of figure 1). The energy extension introduces another set of uncertainties, which, to our knowledge, has not been quantified. These uncertainties are specific to each MRIO. For instance, the extension matrix in EXIOBASE (Kuenen et al. 2013) is derived from the International Energy Agency extended energy balances and from many auxiliary data sources, such as FAOSTAT agriculture and forestry data or international trade and transport data. The energy balances are first converted to match a standard environmental accounting rule (i.e., the System of Environmental-Economic Accounting) and then disaggregated/allocated to the industry categories in the MRIO model using the auxiliary data sets.

Comprehensive analyses on characterizing uncertainty in household footprinting are few and typically qualitative. Wiedman (2009) presented a nice summary of this literature. Lenzen (2000) listed sources of uncertainties in general I-O analysis, which are source data, imports assumption, estimation of capital flow, proportionality assumption, aggregation, allocation, and truncation of downstream life cycle. Weber (2008) indicates that major uncertainties in MRIO models arise from aggregation/disaggregation across different sectoral schemes, treatment of the rest-of-world region, and the choice of currency conversion scheme. He concludes that the benefit of using MRIOs can be undermined by the large uncertainties in cases where a small number of highly disaggregated commodities are modeled. Moreover, trade statistics are inherent sources of biases and errors (Lenzen et al. 2004b).

More recently, some studies use Monte Carlo simulations to comprehensively quantify uncertainties in carbon footprints from final consumption (in aggregate) using MRIOs (Lenzen et al. 2010; Wilting 2012). Lenzen and colleagues (2010) show that overall uncertainties amount to around 20% of total consumer emissions (with 2 standard deviations around the mean) in the UK in a given year. Notably, none of these studies

Table 1 Uncertainties in estimating household (or consumer) energy footprints

Component	*Sources of uncertainty*	*Related studies*[a]	*Our scope*
Consumption expenditure survey (CES)	• Faulty sampling • Recall bias • Changes in survey design • Poor supervision • Nonresponses	(Deaton 2005)	No
Bridge between CES and MRIO model	• Harmonization of disparate item definitions • Disaggregation/allocation of expenditure to sectors • Conversion from purchaser (CES) to basic prices (I-O) • Discrepancy in aggregate household demand	None	Yes
MRIO model	• Source data • Harmonization of sector definitions and aggregation across countries • Treatment of the rest-of-world region • Currency harmonization	(Lenzen 2000; Lenzen et al. 2004b; Lenzen 2011; Peters, 2007; Weber, 2008; Wiedmann, 2009) (Lenzen et al. 2010; Wilting 2012)[b]	No
Energy extension matrix	• Source energy balance data • Environmental accounting scheme (treatment of transportation) • Disaggregating and allocating sectors and carriers	(Usubiaga and Acosta-Fernández 2015)	No

[a]The shown list of studies are key contributions, not an exhaustive set.
[b]These two use a Monte Carlo simulation to characterize uncertainty.
MRIO = multiregion input-output; I-O = input-output.

addresses uncertainty in the link to household surveys. Thus, the uncertainties we analyze in this paper are additional to what they report. We summarize the sources of uncertainties identified in the literature in table 1.

Scope of This Study

In this study, we examine the uncertainties in the process of linking MRIOs and consumer expenditure surveys (CES). We present a novel method to generate distributions of energy intensities, and investigate sensitivities to key data assumptions in bridging household surveys and MRIO. We select as cases India and Brazil, two large and fast-growing economies, whose data are relatively easy to access and who are at different stages of industrialization. We link the CES from the respective countries to EXIOBASE, an MRIO which boasts the highest harmonized sectoral disaggregation among many MRIOs (Inomata and Owen 2014; Wood et al. 2014).[1]

We address the following questions:

- What is the range of uncertainty in household footprints arising from knowledge gaps in bridging household surveys to MRIO? Where do these uncertainties arise?
- How does this uncertainty vary by income level and industrial structure (in two different countries)?
- What is the effect of sectoral aggregation on household footprint estimates?

The rest of the article is organized as follows. We first present our data sources and then summarize our methodology for characterizing and quantifying uncertainty. We then present the results and discuss the implications for policy and for further research.

Data

We adopt the most recent EXIOBASE project (Compiling and Refining Environmental and Economic Accounts) for the year 2007, because EXIOBASE has the highest level of harmonized sectoral disaggregation among MRIOs. This enables a more direct mapping to household consumption categories and a relatively detailed representation of developing countries' consumption patterns. We leave the investigation of uncertainty with other types of MRIO for further research. For the household expenditure data, we use the NSS (National Sample Survey) 2011–2012 (68th round) for India and the POF (Pesquisa de Orçamentos Familiares), the Brazilian counterpart, for 2008–2009. Since EXIO is available for 2007, we assume the industry structure and technology stay the same, and make appropriate currency inflation and exchange rates conversions to harmonize currencies.

Methodology

Brazil and India use their own classifications of household consumption. EXIOBASE is built on 200 commodity sectors derived from the ISIC (International Standard Industrial Classification of All Economic Activities). Uncertainty arises from the lack of information on how to allocate consumption expenditure in each consumption category to the commodity sectors in the I-O model. For example, US$1 expenditure by a household on bread and cereals needs to be allocated to one or many commodity sectors (e.g., rice, wheat, other grains, or other food products) in the ISIC in proportions that reflect the actual financial flows from bread and cereals sales, when no further information is available.

Bridging Household Consumption to Multiregional Input-Output Sectors

There are four broad tasks in bridging household consumption to production sectors in MRIO models: The first is to qualitatively map consumption sectors to those of the I-O; the second is to translate purchaser prices in surveys to basic prices in the I-O; the third is to estimate the allocation consumption expenditure across the mapped sectors in the I-O; and the fourth is to match total household expenditure between the survey and national accounts in the I-O. There are knowledge gaps in all four, but there are more data to draw on from literature in the first task than in the others. Our strategy is therefore to adopt third-party classifications to reduce subjective judgment in the qualitative mapping process. We conduct a sensitivity on the price conversion assumptions based on limited available data for the case of Brazil.

For the uncertainty in allocation shares across sectors, we develop a procedure that we call Randomized Iterative Proportional Fitting Procedure (rIPFP), which is a Monte Carlo simulation scheme applied to the well-known IPFP (i.e., RAS process) used to balance IOTs (chapter 7.4, Miller and Blair [2009]). The result from this procedure is *N* allocation matrices, each row of which consists of allocation shares summing up to 1, which we then propagate to energy intensities. Details on these tasks are described in supporting information S1 available on the Journal's website.

Finally, total household expenditure calculated from household surveys typically falls short of that found in national accounts (I-O). For our main results, we adjust household expenditures from the surveys ($\mathbf{y}_{adj}$) to match the total final demand by households in the MRIO, instead of using the original expenditures reported in the survey ($\mathbf{y}_0$) (more in supporting information S1 on the Web). This adjustment reveals the uncertainty in the sectoral composition of household expenditure. Considering that other studies likely do not conduct this consistency check, we want to investigate the effect of this adjustment on household footprints for a given set of energy intensities.

We have two versions of the valuation matrix (which maps basic prices in the I-O to purchaser prices in the survey) for Brazil: one from Brazilian IOTs and the other from EXIO. This gives two sets of energy intensity distributions for Brazil, while India will have one. This setup is summarized in table 2, in which we have labeled the scenarios for further reference. In the next section, we present the footprint estimation results based on these different combinations.

Table 2 Scenarios for footprint estimation

		Brazil		*India*
		Valuation		
		EXIO default	*Brazil specific*	*EXIO default*
Total household expenditure	$\mathbf{y}_{adj}$	*defVal-adjFD*	*ownVal-adjFD*	*adjFD*
	$\mathbf{y}_0$	*defVal-orgFD*	*ownVal-orgFD*	*orgFD*

Estimating Primary Energy Intensity per Consumption Category

The final calculation of energy intensity for each consumption category follows using standard environmental I-O analysis, except that the final demand vector of the IOT is replaced with a set of vectors that map to consumption categories in the household survey, as shown in equation (1). For each draw $i \in \{1, 2, \cdots, N\}$, we get a primary energy intensity vector $\boldsymbol{e}_i$ with 164 elements, each of which is for each household consumption category. We then summarize *N* intensity values for each of the 164 categories to acquire an intensity distribution by category. This intensity distribution is calculated as[2]

$$\boldsymbol{f} \cdot (\boldsymbol{I} - \mathbf{A})^{-1} \cdot \mathbf{V} \cdot \hat{\mathbf{R}}_i^{\,T} = \boldsymbol{e}_i, \tag{1}$$

where $\boldsymbol{f}$ is the energy extension matrix, $\mathbf{A}$ is the technical coefficient matrix, $\mathbf{V}$ is the valuation matrix, and $\hat{\mathbf{R}}_i$ is the *i*-th matrix among the *N* allocation matrices mentioned above.

Estimating Primary Energy Footprint per Capita

The energy intensities derived above are used to calculate actual energy footprints for individual households. This is a sum product of the energy intensities and expenditures across all consumption sectors for each survey observation. The household footprint is divided by the household size to yield per capita energy footprints. For convenience, we present these data for income deciles and show the range of resulting energy footprints in each decile.

Estimating the Impact of Sectoral Aggregation

As mentioned, when other I-O models with more aggregated (and fewer) sectors are used, the mapping complexity is reduced significantly, but potentially at the risk of inaccurately estimating energy footprints. We assess the extent of this inaccuracy with an illustrative example of the food and beverage sector. We choose this sector because of its importance, and because the survey items under this category can be transparently aggregated without additional assumptions. We derive one aggregate value for the embodied energy intensity covering the entire food and beverage sector and calculate from it total aggregate footprint per capita for each decile. This result is compared with values from our approach based on intensities estimated for each consumption category. Note that a comprehensive assessment of sectoral aggregation is beyond the scope of this study, but

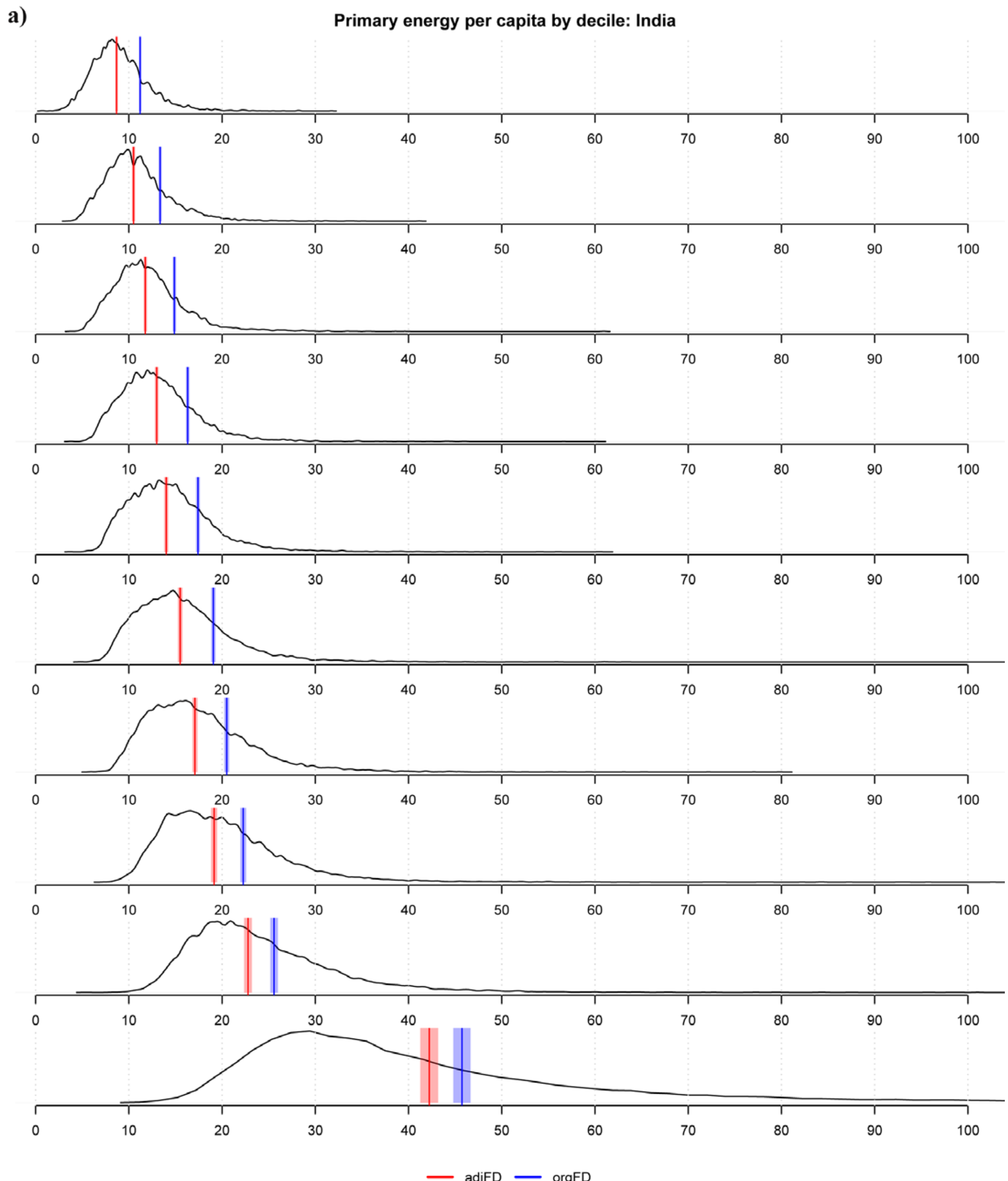

Figure 2 Primary energy footprint by income decile for (a) India and (b) Brazil. The richest decile is at the bottom. The unit is in GJ/capita. The curve is a density function fitted to each corresponding histogram. The colored bars represent ranges of footprint estimates based on the scenarios discussed in table 2. GJ = gigajoules.

should be conducted in future research, and in other countries, so as to determine if there are systematic biases inherent in the aggregation process in other sectors.

Results and Discussion

Primary Energy Footprint per Capita by Income Decile

We show in figure 2 all forms of uncertainty we have estimated in the nationally representative distributions of primary energy consumption per capita by income decile in India and Brazil.[3] The vertical lines show the different means for the four (for Brazil) and two (for India) scenarios laid out in table 2. The shaded areas around the mean shows 2 standard deviations of the distribution of intensities from the allocation shares' uncertainty. Table 3 presents summary statistics for each of these scenarios. The σ values in the table refer to the average of the within-household standard deviations in each decile.

We estimate average household energy footprints per capita (in primary energy terms) of 67.0 gigajoules per capita (GJ/cap)

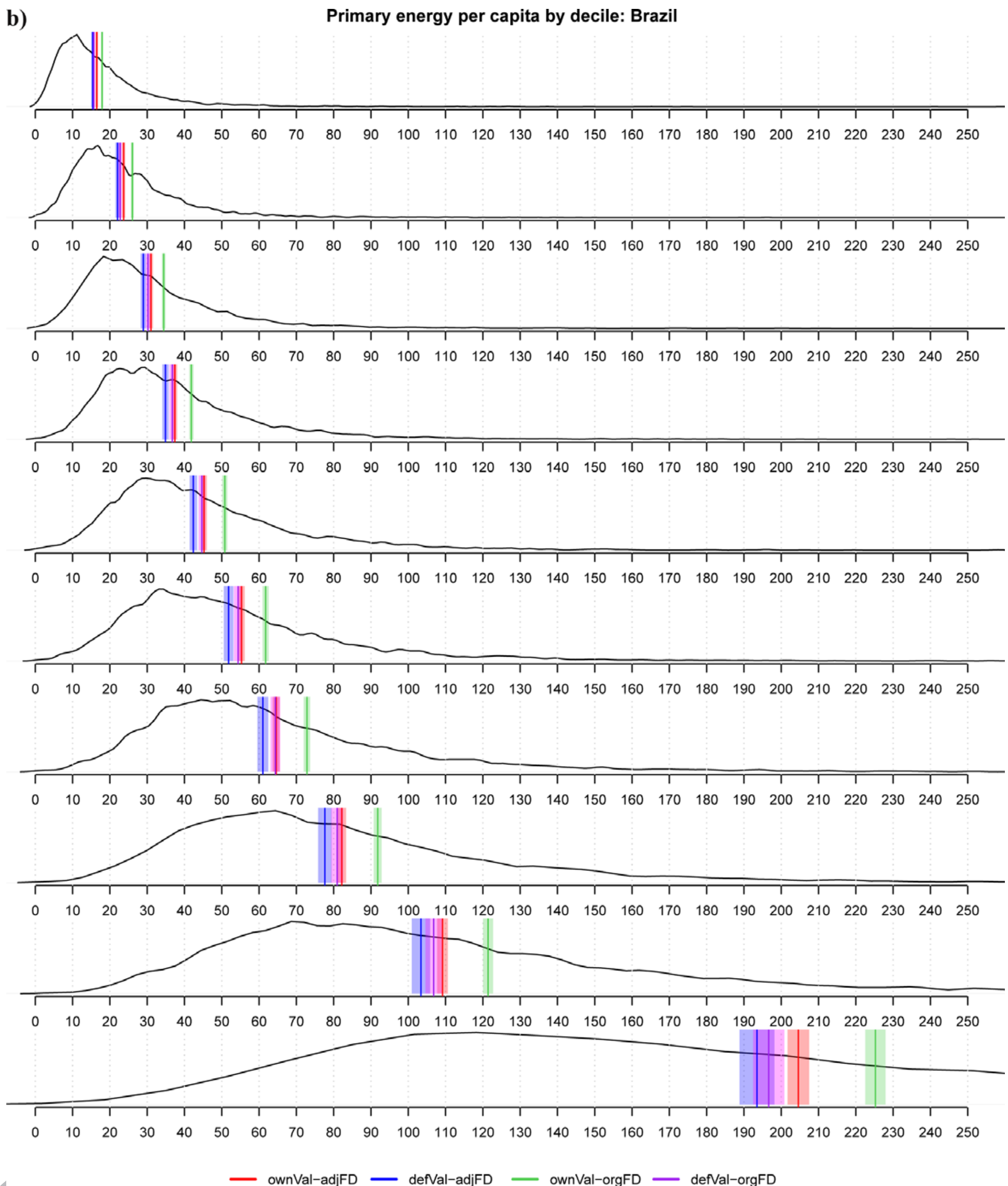

Figure 2 Continued.

and 17.4 GJ/cap for Brazil in 2008 and India in 2011, respectively. Considering historical demand growth, both figures are consistent with previous estimates. Cohen and colleagues (2005) estimate 173.6 GJ per household for Brazil in 1995–1996, which translates to 52.6 GJ/cap, assuming household size of 3.3,[4] and Pachauri (2008) estimates 12.1 GJ/cap for India in 1993–1994. Average primary energy footprint per capita of the lowest income decile is around 16 GJ in Brazil and 10 GJ in India, and for the highest decile is around 200 GJ for Brazil and over 40 GJ for India (table 3).

For both countries, the mean and the range of footprints in a decile increase at an increasing rate. The overall widths of the distributions reflect heterogeneity in household consumption patterns at similar income levels (figure 2). The widths of footprint distributions at higher deciles for India are smaller than those for Brazil, in part because of the use of expenditure-based deciles in the former, which understate inequality by a large margin.[5] Notably, the mean footprint by decile in India does not increase with the income growth as fast as in Brazil, because of high dominance of biomass for cooking, which is relatively income inelastic.

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Table 3 Summary of the per-capita footprint distributions for each case analyzed

		Brazil (GJ/capita)								*India (GJ/capita)*			
	Case	*defVal_orgFD*		*ownVal_orgFD*		*defVal_adjFD*		*ownVal_adjFD*		*orgFD*		*adfFD*	
		μ	(σ)	μ	(σ)	μ	(σ)	μ	(σ)	μ	(σ)	μ	(σ)
Decile	1	15.7	(0.18)	17.9	(0.15)	15.4	(0.20)	16.5	(0.16)	11.2	(0.07)	8.7	(0.07)
	2	22.8	(0.24)	26.0	(0.19)	22.1	(0.27)	23.7	(0.21)	13.4	(0.08)	10.5	(0.08)
	3	30.2	(0.31)	34.4	(0.24)	29.0	(0.34)	31.0	(0.25)	14.9	(0.09)	11.8	(0.09)
	4	36.7	(0.37)	41.8	(0.28)	34.9	(0.41)	37.4	(0.30)	16.3	(0.10)	13.0	(0.10)
	5	44.7	(0.44)	50.8	(0.34)	42.4	(0.49)	45.3	(0.36)	17.4	(0.10)	14.0	(0.11)
	6	54.4	(0.56)	61.8	(0.40)	51.8	(0.63)	55.3	(0.43)	19.1	(0.12)	15.5	(0.12)
	7	64.4	(0.65)	72.8	(0.43)	61.0	(0.72)	64.6	(0.46)	20.5	(0.13)	17.1	(0.14)
	8	80.9	(0.81)	91.8	(0.52)	77.6	(0.90)	82.2	(0.56)	22.3	(0.15)	19.1	(0.16)
	9	106.8	(1.10)	121.4	(0.67)	103.4	(1.22)	109.2	(0.71)	25.6	(0.20)	22.8	(0.21)
	10	196.7	(2.09)	225.2	(1.35)	193.5	(2.33)	204.6	(1.45)	45.7	(0.46)	42.2	(0.48)

Note: The unit is in GJ/capita. The σ value represents the mean of standard deviations for each of households in the decile.
GJ = gigajoules.

Of most importance for this study, we estimate that the combination of uncertainties we analyzed can sway the average per capita energy footprints by 21% and 22% for Brazil and India, respectively. Lenzen and colleagues (2010) estimate uncertainty to be 15% to 20% of the total consumer emissions for the UK case (see figure 9 of their study). Notably, their study quantifies different uncertainties, making our estimates at least conceptually, if not quantitatively, additive.

The adjustment to the scaling of total household expenditure across sectors contributes an 18% change in means in India and up to 11% in Brazil, both in a downward direction. That is, proportionately scaling up household consumption from surveys to match national accounts overestimates consumption in energy-intensive sectors, such as electricity and water (in the case of India) and motor vehicles (in Brazil), which get reallocated to services in our adjustment, including restaurant/hotel and education services (in India) and financial services (in Brazil). The importance of this finding is that the sectoral expenditure allocation implicit in household surveys is inconsistent with that revealed by national I-O data. This has also been previously found in the United States.[6]

The sensitivity in the valuation matrix for Brazil contributes up to a 12% change in mean footprints. The relative direction of the difference does not tell us much because we do not know enough about which scenario better reflects reality. We also test the effect of not converting purchaser prices in the CES to basic prices at all, which, to our knowledge, may well be assumed by others. This overestimates the average footprints by around 18% in Brazil and 14% in India.

Finally, the distribution of intensities from uncertainty in allocating shares of consumption expenditure to production sectors contributes the least. From the standard deviations, we find that it is around 1% of the mean value. This is likely caused by a combination of two factors. First, having ensured that all solutions match the sectoral aggregate expenditure constraints, there are few available solutions, which converge to the same or a narrow range of values. This means certain CES items will have more certain intensity estimates, and in turn footprint estimates (shown as point estimates in figure 3). Second, even in cases where certain CES items have a wider range of intensity estimates, household expenditure on those items are small.

The absolute size of uncertainty is quite predictably largest for the richest decile, and is almost as large in magnitude as the total mean consumption of the lowest decile. This implies that these uncertainties we analyze here have a significant impact on any kinds of energy and carbon footprint analyses linking I-O models with consumer expenditure surveys.

Primary Energy Intensity per Household Consumption Category

All the observations on energy footprints in the previous section are based on the sectoral intensity energy estimates, which are plotted in figure 3.

We observe from these estimates that the magnitude and sectoral allocation of these uncertainties differ between India and Brazil. Overall, the intensities in India have wider uncertainty bands. This may be because the Brazilian survey data are more reliable. The total household expenditure in the survey comprises 60% of that shown in national accounts (compared to 40% in India), and the survey sample share (of total population) is about 2.5 times that of India.

The bulk of the uncertainties are concentrated in the food sectors and the household furnishing and equipment sectors in India, but mainly in the latter in Brazil. The implication of these findings is that uncertainties are not necessarily systematic or generalizable, and need to be investigated for individual countries.

Effect of Sectoral Aggregation

Based on the individual sectoral intensity estimates for India, we estimate the food energy footprints per capita by income decile, as shown in table 4. We observe that the values for the

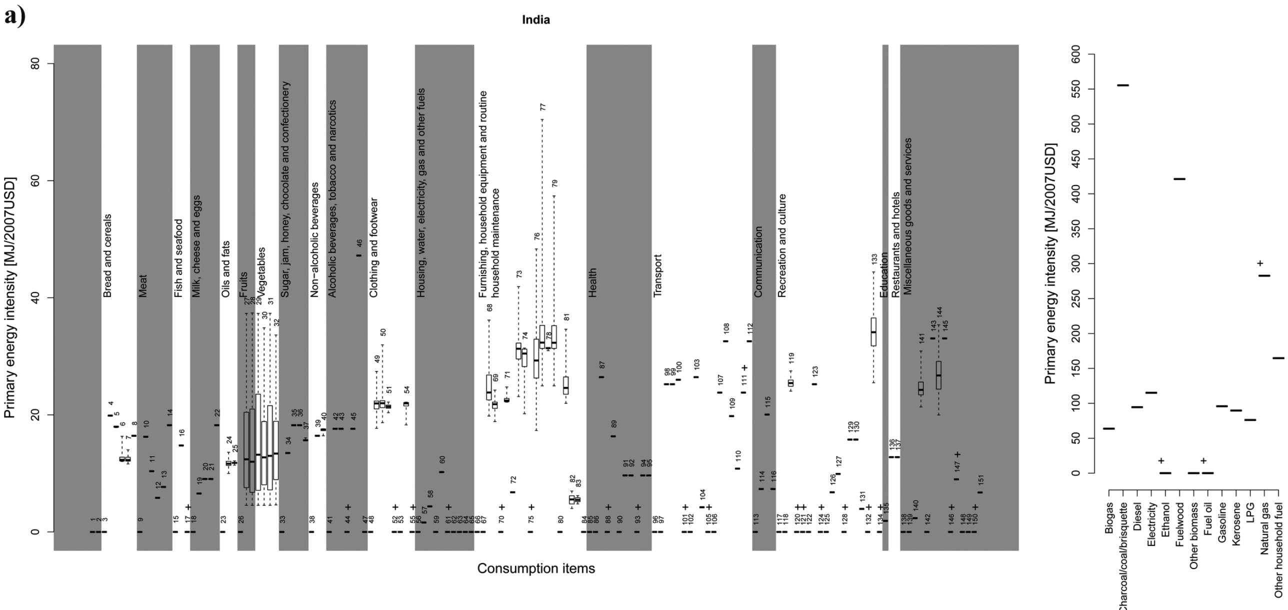

Figure 3 Primary energy intensity by household consumption category. (a) India; (b) Brazil—Brazilian specific valuation; (c) Brazil—EXIO default valuation. We plot nonfuel and fuel items separately because of the vertical scale differences. Items with zero expenditures on the survey side are marked with (+) mark.

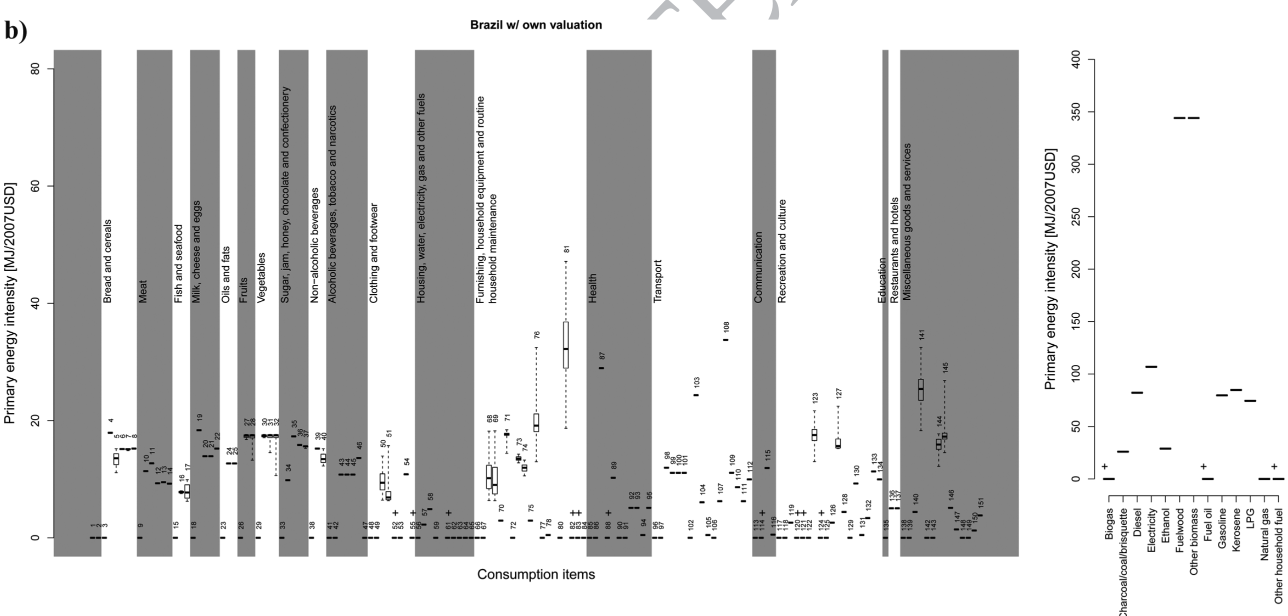

Figure 3 Continued.

aggregate case increase more steeply. Since the composition of food basket for each decile are very different, applying one aggregate intensity value to all deciles' food expenditures yields biased footprint values. For this example for India, we observe the bias amounts to –23 percent for the lowest decile and +10 percent for the highest, compared to the disaggregate case. The direction of the bias will not be generalizable for all countries because it depends on the diet of each country. As mentioned above, we chose the food/beverage sector here for illustration because the aggregation process is simpler than for other sectors. The comparison for other aggregate sectors will entail additional uncertainties related to accurately mapping sectors. Based on the results of the previous section, such an exercise would seem most important for the household furnishing and equipment sectors.

Limitations and Further Work

We adopted third-party sector classifications to map consumption categories to production categories. However, it is

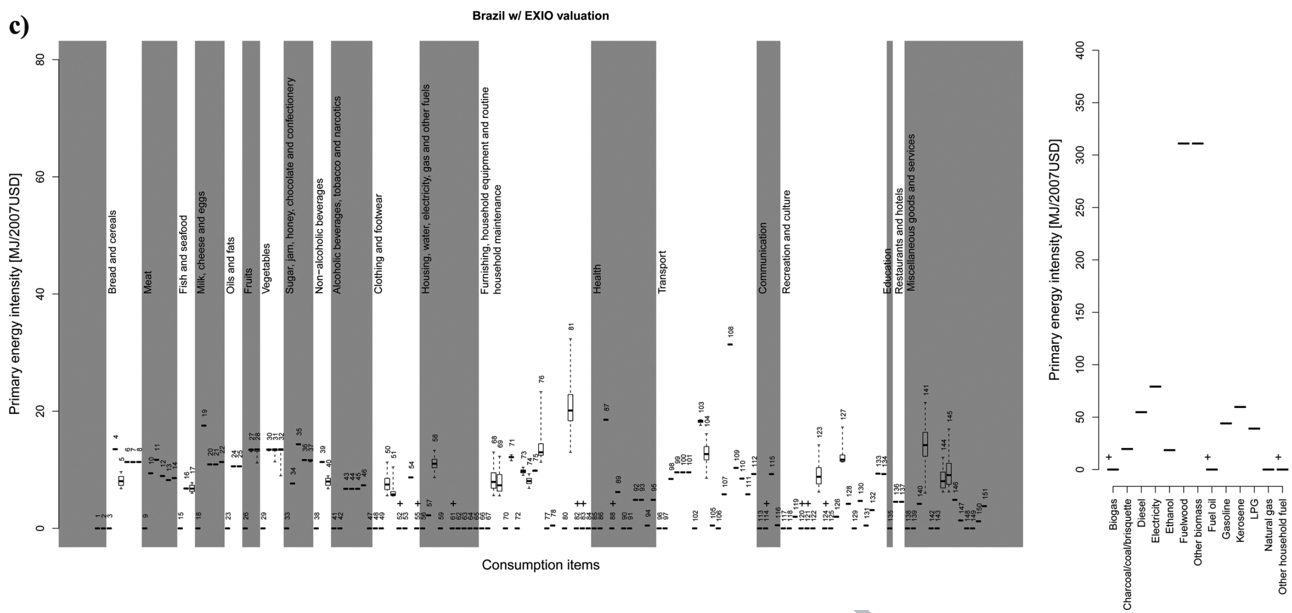

Figure 3 Continued.

Table 4 Estimates for average energy footprint per capita [GJ/cap] in food/beverage consumption in India based on different levels of sectoral aggregation

Decile	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Aggregated sectors	1.7	2.2	2.5	2.8	3.2	3.5	3.9	4.4	5.2	7.0
Disaggregated sectors	2.2	2.7	3.0	3.2	3.5	3.7	4.0	4.4	4.9	6.4

Note: GJ = gigajoules.

possible that these mappings differ by country. To make this analysis more comprehensive, there is a further need to analyze the impacts of changes in the assumption on the structure of the concordance matrices that map the sectoral classifications of the survey data and the I-O model.

Furthermore, our analysis starts from proportionately scaling up the household expenditure from the survey to match the household final demand total from the national account. We recognize that different types of survey items may need to be scaled disproportionately even before the rIPFP process mainly to incorporate more realistic patterns of reporting behavior for different items.

Additional information about market structure and supply chains may narrow the distributions derived from the random allocation shares. But considering the relatively small influence of the allocation uncertainty, these additional details will not contribute significantly to the final footprint results.

Different population groups face different prices for major food items. Since carbon footprints are derived from reported expenditures, footprints of people paying higher prices would be overestimated. We investigate this issue in future work.

This methodology is replicable and should be applied across time and to other countries to determine if the range of uncertainties found here are systematic.

Conclusions

We have presented a novel approach to link consumer expenditure survey data to an MRIO model and assess uncertainties from data gaps in this process. We have focused on assessing household energy footprints, but this method is applicable to any social or environmental impact analysis of household consumption. This article quantifies the uncertainty arising from the lack of information on how to allocate expenditure in consumption surveys to industrial sectors, how to match their respective valuation bases, and how to scale expenditures in consumption sectors to match national accounts. Notably, the error associated with scaling and matching aggregate expenditure is an order of magnitude greater than the uncertainty from the allocation shares.

We have applied this methodology to analyze household energy footprints of two big and fast-growing economies: Brazil and India. Our result shows that the combination of the uncertainties we have studied can contribute up to over 32% of average energy footprint estimates for the highest income deciles in India and over 22% for those in Brazil. For the whole population, the average extent of uncertainty in household energy footprints is similar for the two countries, at around 21%. Considering the nonlinear increase of expenditure in the upper income deciles, this implies the uncertainties analyzed in this article can play a very important role in footprint analyses based on MRIO models, particularly for rich populations.

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Richard Wood and Gibran Vita at the Department of Energy and Process Engineering of Norwegian University of Science and Technology provided assistance and shared information on EXIOBASE and its development. Professor Joaquim J.M. Guilhoto at Departamento de Economia of Universidade de São Paulo shared Brazilian national I-O and valuation data, which Luís Gustavo Tudeschini helped translate.

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Notes

1. This assumes of course that we place some confidence in the EXIO data. We have done considerable due diligence on the data, including in-depth conversations with the source team on methods, and limited comparisons to national IOTs, which, in the case of Brazil and India, have higher sectoral representation than traditional MRIOs.
2. For simplification, we omitted in the equation the process of breaking down $\boldsymbol{V} \cdot \hat{\mathbf{R}}_i^{\,T}$ into other 48 regions in the EXIO (9,600 sectors in total) and summing them back to acquire intensities for 164 consumption categories.
3. The NSS survey for India does not have an income field in its household characteristics. We use the total household expenditure as a proxy for income. More details are provided in figure S2-1 in supporting information S2 on the Web. National representativeness is achieved by applying the sampling weights in the survey.
4. From the POF survey, we find the average household size in 2009 is 3.3.
5. The expenditure-based Gini coefficient for India was ~40 in the NSS 11-12, but the Gini calculated from income data for India in 2004–2005 was ~56 (the India Human Development Survey, the only known survey for India that solicited information on income). Author calculations.
6. See Bureau of Labor Statistics article on www.bls.gov/cex/cepceconcordance.htm, retrieved last on 21 September 2016.

References

Cohen, C., M. Lenzen, and R. Schaeffer. 2005. Energy requirements of households in Brazil. *Energy Policy* 33(4): 555–562.

Deaton, A. 2005. Measuring poverty in a growing world (or measuring growth in a poor world). *Review of Economics and Statistics* 87(1): 1–19.

Inomata, S. and A. Owen. 2014. Comparative evaluation of MRIO databases. Economic Systems Research 26(3): 239–244.

Ivanova, D., K. Stadler, K. Steen-Olsen, R. Wood, G. Vita, A. Tukker, and E. G. Hertwich. 2016. Environmental impact assessment of household consumption. *Journal of Industrial Ecology* 20(3): 526–536.

Kok, R., R. M. J. Benders, and H. C. Moll. 2006. Measuring the environmental load of household consumption using some methods based on input-output energy analysis: A comparison of methods and a discussion of results. *Energy Policy* 34(17): 2744–2761.

Kuenen, J., J. Acosta-Fernández, A. Usubiaga, and D. Wittmer. 2013. Report on Update EXIOPOL Emissions Database: EXIOBASE consortium D6.1. Q8

Lenzen, M. 1998. Primary energy and greenhouse gases embodied in Australian final consumption: An input-output analysis. *Energy Policy* 26(6): 495–506.

Lenzen, M. 2000. Errors in conventional and input-output–based life-cycle inventories. *Journal of Industrial Ecology* 4(4): 127–148.

Lenzen, M. 2011. Aggregation versus disaggregation in input–output analysis of the environment. *Economic Systems Research* 23(1): 73–89.

Lenzen, M., C. Dey, and B. Foran. 2004a. Energy requirements of Sydney households. *Ecological Economics* 49(3): 375–399.

Lenzen, M., A. Geschke, T. Wiedmann, J. Lane, N. Anderson, T. Baynes, J. Boland, et al. 2014. Compiling and using input–output frameworks through collaborative virtual laboratories. *Science of the Total Environment* 485–486: 241–251.

Lenzen, M., L.-L. Pade, and J. Munksgaard. 2004b. CO_2 multipliers in multi-region input-output models. *Economic Systems Research* 16(4): 391–412.

Lenzen, M., and G.M. Peters. 2010. How city dwellers affect their resource hinterland. *Journal of Industrial Ecology* 14(1): 73–90.

Lenzen, M., M. Wier, C. Cohen, H. Hayami, S. Pachauri, and R. Schaeffer. 2006. A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. *Energy* 31(2–3): 181–207.

Lenzen, M., R. Wood, and T. Wiedmann. 2010. Uncertainty analysis for multi-region input-output models—A case study of the UK's carbon footprint. *Economic Systems Research* 22(1): 43–63.

Liu, H.-T., J.-E. Guo, D. Qian, and Y.-M. Xi. 2009. Comprehensive evaluation of household indirect energy consumption and impacts of alternative energy policies in China by input-output analysis. *Energy Policy* 37(8): 3194–3204.

Miller, R. E. and P. D. Blair. 2009. *Input-output analysis: Foundations and extensions*. Cambridge, UK; New York: Cambridge University Press, 784 pp.

Minx, J., G. Baiocchi, T. Wiedmann, J. Barrett, F. Creutzig, K. Feng, M. Förster, P.-P. Pichler, H. Weisz, and K. Hubacek. 2013. Carbon footprints of cities and other human settlements in the UK. *Environmental Research Letters* 8(3): 035039.

Pachauri, S. and D. Spreng. 2002. Direct and indirect energy requirements of households in India. *Energy Policy* 30(6): 511–523.

Park, H.-C. and E. Heo. 2007. The direct and indirect household energy requirements in The Republic of Korea from 1980 to 2000—An input-output analysis. *Energy Policy* 35(5): 2839–2851.

Peters, G. P. 2007. Opportunities and challenges for environmental MRIO modeling: illustrations with the GTAP database. In 16th International Input-Output Conference, 2–6 July, Istanbul, Turkey.

Peters, G. P., J. C. Minx, C. L. Weber, and O. Edenhofer. 2011. Growth in emission transfers via international trade from 1990 to 2008. *Proceedings of the National Academy of Sciences of the United States of America* 108(21): 8903–8908.

Steen-Olsen, K. 2015. Integrated economic and physical information for environmental footprint modelling. Q9

Steen-Olsen, K., R. Wood, and E. G. Hertwich. 2016. The carbon footprint of Norwegian household consumption 1999–2012. *Journal of Industrial Ecology* 20(3): 582–592. Q10

Usubiaga, A. and J. Acosta-Fernández. 2015. Carbon emission accounting in MRIO models: The territory vs. the residence principle. *Economic Systems Research* 27(4): 458–477.
Weber, C. L. 2008. Uncertainties in constructing environmental multiregional input-output models. In International input-output meeting on managing the environment, 1–31.
Q11
Wiedmann, T. 2009. A review of recent multi-region input-output models used for consumption-based emission and resource accounting. *Ecological Economics* 69(2): 211–222.
Wilting, H. C. 2012. Sensitivity and uncertainty analysis in MRIO modelling; Some empirical results with regard to the Dutch carbon footprint. *Economic Systems Research* 24(2): 141–171.
Wood, R., K. Stadler, T. Bulavskaya, S. Lutter, S. Giljum, A. de Koning, J. Kuenen, et al. 2014. Global sustainability accounting—Developing EXIOBASE for multi-regional footprint analysis. *Sustainability* 7(1): 138–163.

Supporting Information

Supporting information is linked to this article on the *JIE* website:

Supporting Information S1: This supporting information S1 describes each step of the process adopted for the methodology. At the end, it includes further explanation of the Randomized Iterative Proportional Fitting Procedure (rIPFP).

Supporting Information S2: This supporting information S2 provides more details on the data used in the analysis.