








Prioritizing Consumption-Based Carbon Policy Based on the Evaluation of Mitigation Potential Using Input-Output Methods


Richard Wood ¹, Daniel Moran ¹, Konstantin Stadler ¹, Diana Ivanova ¹,
Kjartan Steen-Olsen ¹, Alexandre Tisserant ¹ and Edgar G. Hertwich ^{1,2}

¹Industrial Ecology Programme (IndEcol), NTNU, NO-7491 Trondheim, Norway

²Yale School of Forestry and Environmental Studies, New Haven, CT 06511

Keywords:

carbon footprints
climate policy
industrial ecology
input-output analysis
life cycle assessment (LCA)
rebound

 Supporting information is linked to this article on the JIE website

Summary

Carbon footprints aim to engage consumers in contributing to climate-change mitigation. Consumption-oriented policy measures attempt to cause voluntary or incentivized interventions that reduce environmental impact through the supply chain by utilizing demand drivers. A large body of life cycle assessment studies describe how specific actions can reduce the environmental footprint of an individual or household. However, these assessments are often conducted with a narrow focus on particular goods and processes. Here, we formalize a counterfactual method and operational tool for scoping the potential impact of such actions, focusing on economy-wide impact. This “quickscan” tool can model shifts and reductions in demand, rebound effects (using marginal expenditure), changes in domestic and international production recipes, and reductions in the environmental intensity of production. This tool provides quick, macro-level estimates of the efficacy of consumer-oriented policy measures and can help to prioritize relevant policies. We demonstrate the method using two case studies on diet and clothing using the EXIOBASE3 multiregional input-output database, giving spatially explicit information on where environmental impact reductions of the interventions occur, and where impacts may increase in the case of rebounds.

Introduction

Recent work suggests that changes in lifestyles and consumer choice are necessary to reduce environmental pressures (Gardner and Stern 2008; Baiocchi et al. 2010; Girod et al. 2014; Munksgaard et al. 2005; Ivanova et al. 2016). Environmental footprints, based on consumption-based accounting, have been used to quantify the environmental benefits accrued by various consumption choices. Footprint assessments

can help consumers “green” their consumption through shifts in their consumption (Gardner and Stern 2008; Girod et al. 2014; Lenzen and Dey 2002). Such approaches have been driven by analyses around carbon footprints (Weber and Matthews 2008; Hertwich 2011; Minx et al. 2009; Jones and Kammen 2011) and personal footprint calculators (West et al. 2016). A life cycle approach (Finkbeiner 2009; Weidema et al. 2008) is taken implicitly in the calculation of footprints, and, as such environmental footprints have emerged as a useful concept for

Conflict of interest statement: The authors have no conflict to declare.

[The article was corrected after initial online publication to include missing Orcid ID links.]

Address correspondence to: Richard Wood, Industrial Ecology Programme (IndEcol), NTNU, NO-7491 Trondheim, Norway. Email: richard.wood@ntnu.no, Web: www.environmentalfootprints.org

© 2017 The Authors. *Journal of Industrial Ecology*, published by Wiley Periodicals, Inc., on behalf of Yale University. This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
DOI: 10.1111/jiec.12702

Editor managing review: Arnold Tukker

individuals, populations, and other end-user groups to consider their individual or collective consumption and to analyze which items of consumption embody the most environmental impact.

However, when looking at how consumers can actually drive change, environmental footprints reach a limit. It is expected that changes in consumption patterns can drive changes in impacts from production, but the cause and effect mechanism is not well elucidated. It has been argued that changing gross consumption patterns offer a similar or even larger potential reduction of environmental load than improving the environmental efficiency of the economy (O'Rourke 2014; Barrett and Scott 2012). Consumption-based policy may cause change in several respects: Conditions for product development and/or marketing strategies may change; the types of products that consumers demand may change (including shifting to locally produced or green alternatives); and the level of demand from consumers may change (see discussion in Schanes et al. [2016]).

A significant body of work exists at the micro level based on life cycle assessment (LCA): for example, from assessing the impacts from changing transport habits (Borken-Kleeefeld et al. 2013; Chester and Horvath 2009); shifting from a meat-based to a vegetarian or vegan diet (Baroni et al. 2007; Meier and Christen 2013); and home energy savings (Gardner and Stern 2008) to other achievable behavioral changes (Jones and Kammen 2014; Dietz et al. 2009). LCA is an appropriate tool at the micro level (Girod and de Haan 2009; Steen-Olsen and Hertwich 2014), but to ensure a consistent quantification of life cycle impacts at the scale that matters to the climate problem, input-output (I-O) analysis (IOA) has been applied in most assessments of consumer environmental impacts (Hertwich 2011).

IOA utilizes aggregated historic accounts, and hence hybrid techniques have been developed in order to disaggregate sectors in order to model specific changes in the production structure (Malik et al. 2014). Hybrid IO-LCA techniques disaggregate sectors in an I-O table (IOT) using LCA data, e.g. splitting a broad "food products" sector into several component subsectors (compare Wood et al. [2014] and Gibon et al. [2015]). Changes to demand or production processes can then be modeled in the disaggregated supply chains. The disaggregation approach is powerful, but also quite data and labor intensive; it requires the full amount of process/product-specific data for each product being disaggregated. Alternatives to extensive disaggregation of IOTs have been proposed previously focusing on the individual supply chain (Lenzen and Crawford 2009). I-O models offer a framework to assess the economy-wide effects of changes in technologies or consumption patterns; see, for example, the account given by Wilting and colleagues (2008). Takase and colleagues (2005) used this approach to study the effect on emissions from a shift in preferred transportation modes among households, among other cases. Barrett and Scott (2012) applied an I-O model of the United Kingdom to assess the potential emissions reduction potential of several strategies at both consumer and producer levels toward 2050. We further this and associated work by formalizing a macro-level framework to model interventions, modifying production recipes and demand

variables, taking into account feedbacks within the global supply chain, and making it feasible to compare several intervention options simultaneously within one consistent framework.

One strength of using a global multi-regional I-O (MRIO) table is that the study can consider all supply chains, so an intervention at the production or consumption end of a supply chain will be linked, globally, to the other end of that chain. Drawbacks to both LCA and I-O methods include (1) they are static, not dynamic (see, e.g., Barker et al. [2009] for use of I-O in dynamic frameworks), (2) they have fixed linear production functions, and (3) do not model behavioral responses in the most simple formulation (we relax this for consumers here). The results must be understood as a comparison between the status quo and a scenario in which the intervention, *ceteris paribus*, has been achieved. Hence, while I-O and LCA frameworks do not consider any dynamic response of the economy such as in, for example, computable general equilibrium models (Dixon and Jorgenson 2013), they do provide clarity of first-order impacts devoid of effects of assumptions about substitution elasticities, utility and profit maximization, price equilibrium, etc. (West 1995).

The I-O-based model developed here describes a general method seeking to offer economy-wide life cycle calculations of the impact of consumption-oriented policies affecting changes in volume and mix of consumption patterns. It does not seek to capture the behavioral response of economic actors, such as additional innovation in the desired direction or price-based responses, which would require computable general equilibrium, or other dynamic macro-economic models (Rose 1984; Pfaff and Sartorius 2015). Of interest for consumption-based policy, however, is the potential response consumers *may* have, and we hence offer calculations of the indirect rebound effect of the final consumer (Hertwich 2005; Sorrell 2009). The indirect rebound effect of final consumers describes the phenomenon by which households use money saved by demand reduction or more efficient consumption and spend that newfound income on other, potentially environmentally worse, goods and services. Estimates of the marginal unit of consumption in I-O models (Font Vivanco et al. 2014) provide a straightforward way to estimate the level of indirect rebound.

This paper fills a gap in the literature on methods to connect life cycle approaches to consumption-based interventions at the macro level. We focus here on elucidation of method, discussing types of interventions and how consumer rebound is treated. Two case studies, concerning food and diets, and clothing are presented to illustrate the method. In supporting information S1 available on the Journal's website, we provide the data and code. Finally, we discuss limitations to the model and conclude.

Methods

Three main options exist for consumption-based policy interventions: (1) changing consumption patterns including reduction of overall consumption; (2) modifying the inputs required for production in the industry (e.g., changing import

partners or modifying the recipes of production); and (3) reducing direct emissions through, for example, pollution control or improved efficiency. A specific policy intervention can potentially rely on any combination of these three options. In this method, we evaluate changes which may be prompted by various different policies; for example, we consider the effect of decreased meat consumption, though this may be incentivized through a healthy eating policy, a low-GHG (greenhouse gas) diet policy, or otherwise. A framework that directly aligns with these needs is the environmentally extended multi-regional input-output (EE-MRIO) model (Minx et al. 2009). I-O models that follow the Leontief demand-driven approach (Leontief 1970) calculate the supply-chain environmental impact due to a certain quantity of final demand.

Environmentally Extended Multiregional Input-Output Analysis

Environmentally extended IOA links environmental pressure data (e.g., GHG emissions, water extraction, etc.) of economic activities to the final consumer of the produced commodities. This follows the classic Leontief demand-style modeling (Leontief 1970) based on a product-by-product matrix in which the total output \mathbf{x} required for a certain final demand vector \mathbf{y} for the region or country under consideration is (equation 1):

$$\mathbf{x} = \mathbf{L} * \mathbf{y} \quad (1)$$

where \mathbf{L} is the Leontief inverse given by (equation 2):

$$\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} \quad (2)$$

and \mathbf{A} being the direct coefficient matrix (showing product inputs per unit product output) while \mathbf{I} is an identity matrix of appropriate size. The use of a square product-by-product table entails assumptions about allocation of inputs for co-produced products, as discussed by Majeu-Bettez and co-authors (Majeu-Bettez et al. 2014, 2016). While the derivation below is easily generalizable for supply-and-use systems, we simplify the mathematics for use in square IOTs. In this work, we look solely at household actions, and thus household consumption \mathbf{y} (for most countries, household consumption is in the order of 60% to 70% of total final demand [Ivanova et al. 2016]). We use an EE-MRIO setup, however the derivation is the same for domestic analyses, with appropriate treatment of imports and exports (Wood and Dey 2009; Tukker et al. 2013).

Environmental pressures are linked to the I-O framework through a row vector \mathbf{s} of environmental stressors per unit output. This allows to calculate overall upstream impacts (footprints \mathbf{d}) due to household consumption \mathbf{y} by (equation 3):

$$\mathbf{d} = \mathbf{s} * \mathbf{L} * \mathbf{y} + \mathbf{1h} \quad (3)$$

with \mathbf{h} giving the direct environmental pressure of final demand by product and region (e.g., direct emissions from gas cooking) and $\mathbf{1}$ a vector of ones of appropriate size used for summation. The footprints \mathbf{d} are then based on the household consumption \mathbf{y} in one specific region that summarize all domestic and imported environmental stressors occurring during production and define

the reference scenario for the comparison of the intervention effects.

Linking Lifestyles and Interventions of Policy to Environmentally Extended Multiregional Input-Outputs

In order to link the three types of policy/lifestyle interventions to the EE-MRIO framework, interventions need to be formalized in terms of the variables of the model. We reference modified variables by superscripts. Subscripts are used for indexing sectors, regions, and products. A summary of variables and indices used in this section is given in table 1.

[The article was corrected after initial online publication to include the missing text directing readers to table 1.]

Consumption Pattern Change or Consumption Reduction, and Rebound

Policies can aim to change consumption patterns by either focusing solely on the reduction of consumption of goods or on shifting consumption to other demand categories.

In the first case, the reduced final demand \mathbf{y}^{red} is given by (equation 4):

$$\mathbf{y}^{\text{red}} = \mathbf{y} \odot (1 - \mathbf{q}^y \odot \mathbf{t}^y) \quad (4)$$

where \odot represents element-wise multiplication and the vector \mathbf{q}^y specifies the technically possible reduction for each consumer good and \mathbf{t}^y the corresponding assumed penetration rate (both ranging from 0 to 1).

There may be a considerable difference between the goal or the technically achievable potential of an intervention and the likely actual penetration of that intervention. For example, it may be a goal for a population to reduce its meat consumption by 50% (\mathbf{q}^y), but based on market surveys, observations, behavioral analysis, and the like, we may forecast that only 10% of the population will make such a change, and thus the actual reduction will be closer to 5%. We use a penetration rate $\mathbf{t}^y < 1$ in order to attenuate between the technically achievable and the likely actual impact of the intervention.

In the case of an intervention focusing on shifting consumption patterns, the reduced consumption of one product (i) is substituted by another (g being the products with increased demand). As these products may differ in price, we include relative price differences p between the product groups, with no price differences having a unitary value. In our model, increased demand is modeled by distributing the increase according to the country's marginal consumption pattern of all products unaffected by the specific policy intervention (Lenzen and Dey 2002; Murray 2013; Font Vivanco and van der Voet 2014). The marginal expenditure shares of consumption were estimated by using a database of expenditure elasticities developed for EXIOBASE (Tisserant et al. 2017; Wood et al. 2015). The elasticities were obtained by splitting EXIOBASE household final consumption in 2010 using information from consumer expenditure surveys that provide information on expenditure pattern at different income level of consumer units (including replicating, handling under-/over-reporting, etc.; for full details, see

Table 1 A summary of variables and indices used in the *Linking Lifestyles and Interventions of Policy to Environmentally Extended Multiregional Input-Outputs* section

Variable	Description
r	Set of countries/regions of the model
m	Set of products of the model
n	Column index of the set of region-product combination of the Cartesian product of regions and sectors ($n \in rm$). Used for columns only.
o	Row index of the set of region-product combination of the Cartesian product of regions and sectors ($o \in rm$). Used for rows only.
z	Total number of region - product combinations in the model. $z = r \times m $
i	Set of countries/products (row dimension) effected by reduction of a specific option ($i \in z$)
j	Set of countries and products (columns) effected by an specific option ($j \in z$)
g	Set of countries and products effected by any substitution ($g \in z$)
red	Reduced values due to a direct reduction by an intervention
sub	Increase of a value due to a substitution effect of an intervention
mar	Marginal consumption shares of household consumption
reb	Increase of a value due to a rebound effect caused by an intervention
int	Effect of a single intervention in a policy package.
tot	Total effects of a policy package comprising several policy interventions
x	Industry/Product output, column vector of size (z)
y	Final demand per product, column vector of size (z). y^h refers to household consumption component of final demand. Other superscript text identifies intervention effects due to a change in the final consumer behavior.
A	Symmetric technical coefficient matrix of size (z,z). Superscript text identifies intervention effects due to a change in the interindustry structure.
a	One column vector of the technical coefficient matrix A ; size (z)
L	Leontief inverse of A , size (z,z)
$\mathbf{1}$	Vector of ones (size z), can be used for summation.
I	Identity matrix of size (z,z)
s	Environmental stressors per unit output; row vector of size (z). Superscript text identifies intervention effects due to a efficiency improvements.
h	Direct environmental interventions of final demand by product; column vector of size (z); as superscript for y^h , refers to household consumption component of final demand
d	Calculated footprint of the region under consideration; scalar.
b	Global total improvement in relation to the original state; scalar.
p	Scalar of price differences
q	Targeted intervention effect per q^y) final demand – column vector of size (z); q_j^A) interindustry structure – column vector of size (z) for each effected industry j ; q^s) efficiency improvements – row vector of size (z)
t	Penetration rate – assumed uptake rate per sector/product of q t^y) final demand – column vector of size (z); t_j^A) interindustry structure – column vector of size (z) for each effected industry j ; t^s) efficiency improvements – row vector of size (z)

Tisserant et al. [2017]). From this income-based split of EX-IOBASE household final consumption, we estimated product-specific total expenditure elasticities and marginal spending shares y^{mar} using the log-log model (Haque 2006; Grabs 2015), where y^{mar} sums to 1 for each column. Finally, the additional final demand due to the substitution effect y^{sub} is estimated by (note that the calculation is done for each product of the system o) (equation 5):

$$y_o^{sub} = p (\mathbf{1y} - \mathbf{1y}^{red}) \frac{y_o^{mar}}{\sum_g y_g^{mar}} \quad \forall (o \in g)$$

$$y_o^{sub} = 0 \quad \forall (o \notin g) \quad (5)$$

Reducing or changing consumption thus potentially frees money, which consumers may re-spend, diminishing the initial environmental savings. The new consumption due to rebound y^{reb} (for each o) is given by (equation 6):

$$y_o^{reb} = (\mathbf{1y} - \mathbf{1} (y^{red} + y^{sub})) * \frac{y_o^{mar}}{\sum_o y_o^{mar}} \quad \forall o \in m \quad (6)$$

Note that a specific rebound (e.g., if newly available money is supposed to be spent on specific products) can be modeled with the substitution mechanism described in equation (5).

The new household final consumption vector y^{int} is then given by (equation 7):

$$y^{int} = y^{red} + y^{sub} + y^{reb} \quad (7)$$

Modifying Required Inputs

The main goal in modifying the \mathbf{A} matrix consists of reducing the requirements of inputs that eventually cause environmental impacts. Generally, this can be achieved by reducing inputs or shifting requirements to other intermediate inputs or value added (Rose 1984). Any overall reduction (or increase) in inputs will induce a price impact. This first-order effect can be captured in an I-O model, but not the response to the price impact. As such, we purely apply exogenous information on technological substitution to the linear production function. This is consistent with LCA approaches (NEEDS 2009) and allows for consideration of direct impact of an intervention through the economy. We further keep to an open I-O model, ignoring potential feedbacks, for example, between the demand and supply of labor.

Hence, for each technical coefficient (column) vector \mathbf{a} of the \mathbf{A} matrix (of size $z \times z$) effected by an intervention (equation 8):

$$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_z] \quad \forall (n \in j)$$

$$\mathbf{a}_n^{\text{red}} = \mathbf{a}_n \odot (1 - \mathbf{q}_n^{\text{A}} \odot \mathbf{t}_n^{\text{A}}) \quad (8)$$

where the column vector \mathbf{q}_n^{A} specifies the targeted reduction rate for each product sector and \mathbf{t}_n^{A} the corresponding assumed penetration rate (both ranging from 0 to 1). It is important to note that the technological changes induced by \mathbf{q}_n^{A} should be based on knowledge about the available technology and the average technology already described in \mathbf{a}_n , such that \mathbf{q}_n^{A} is the percentage improvement of the available technology versus existing technology (e.g., energy savings due to blast furnace improvements in iron and steel production; compare methods outlined in Rose [1984]).

If substitution of inputs occurs (vegetables for meat), the price-adjusted initial reduction is reapplied to the product set (g) (equation 9):

$$a_{o,n}^{\text{sub}} = p_n (\mathbf{1a}_n - \mathbf{1a}_n^{\text{red}}) \frac{a_{o,n}}{\sum_{o \in g} a_{o,n}} \quad \forall (n \in j) \quad \forall (o \in g) \quad (9)$$

$$a_{o,n}^{\text{sub}} = 0 \quad \forall (n \in j) \quad \forall (o \notin g)$$

with p_n specifying the relative price differences between the products being substituted within one affected industry sector n .

The new technical coefficient vectors are then given by (equation 10):

$$\mathbf{a}^{\text{int}} = \mathbf{a}^{\text{red}} + \mathbf{a}^{\text{sub}} \quad (10)$$

which replace the original \mathbf{a} vectors in the new technical coefficient matrix \mathbf{A}^{int} .

Using MRIO modeling allows for the further inclusion of transport-related effects due to changes in location of product supply. There are two types of changes in transport requirements. The first is the direct requirement of transport, for example, due to purchasing a car produced in Germany versus Korea. Such requirements need to be modeled exogenously (unless a full transport model is integrated) as a direct change in the

input requirements (equation 5 or 8). The second type is the indirect requirement through changes in products consumed (e.g., switching from coal to gas as fuel for electricity generation), and is captured when I-O modeling occurs in basic prices (transport is then modeled as an input into the good being consumed, and any change in consumption of a good necessarily changes the total amount of transport required) (Eurostat 2008).

Improving the Eco-Efficiency

Improvements in the eco-efficiency of a certain industry sector can be modeled by altering the corresponding value in the environmental stressors per unit output vector \mathbf{s} . By (equation 11):

$$\mathbf{s}^{\text{int}} = \mathbf{s} \odot (1 - \mathbf{q}^{\text{s}} \odot \mathbf{t}^{\text{s}}) \quad (11)$$

where the row vector \mathbf{q}^{s} specifies the targeted efficiency improvement rate for each industry sector and \mathbf{t}^{s} the corresponding assumed penetration rate (both ranging from 0 to 1).

Likewise, direct emission reduction for final demand emissions can be modeled by (equation 12):

$$\mathbf{h}^{\text{int}} = \mathbf{h} \odot (1 - \mathbf{q}^{\text{h}} \odot \mathbf{t}^{\text{h}}) \quad (12)$$

Note that there may be a dependency between changes in \mathbf{A} and changes in \mathbf{s} . If an intervention reduces both the amount of fuel use, and its corresponding air emission, then \mathbf{A} and \mathbf{s} must be modified consistently. Such dependencies must be identified and quantified by the analyst exogenously to the model, as they are not automatically captured by this procedure.

Calculating the New Emission Footprints

The new footprint based on a specific policy intervention is given by (equation 13):

$$\mathbf{d}^{\text{int}} = \mathbf{s}^{\text{int}} * (\mathbf{I} - \mathbf{A}^{\text{int}})^{-1} * \mathbf{y}^{\text{int}} + \mathbf{1h}^{\text{int}} \quad (13)$$

which can be calculated for each country/region affected by an intervention (*int*) separately. The global total improvement b considering the original state (footprints) d is then given by (equation 14):

$$b = \frac{d - \sum d^{\text{int}}}{d} \quad (14)$$

Combining Policy Interventions into Intervention Packages

Several policy interventions can be integrated into one comprehensive intervention package. In order to avoid a certain path dependence and/or double counting, for each policy intervention within the package, \mathbf{y}^{tot} , \mathbf{A}^{tot} , \mathbf{s}^{tot} and \mathbf{h}^{tot} must be estimated independently as described above. The final values of the whole package are then given by calculating the differences in value for each single intervention *int* ($\mathbf{y} - \mathbf{y}^{\text{int}}$, for the case of \mathbf{y}), adding them together ($\sum_{\text{int}} (\mathbf{y} - \mathbf{y}^{\text{int}})$) and subtracting these from the original value \mathbf{y} . For example, for the final demand \mathbf{y} (equation 15):

$$\mathbf{y}^{\text{tot}} = \mathbf{y} - \sum_{\text{int}} (\mathbf{y} - \mathbf{y}^{\text{int}}) \quad (15)$$

where y^{tot} , A^{tot} , s^{tot} , and h^{tot} must be constrained positive. Footprints are then calculated as per a single intervention. Important to note is that combining policy interventions can give a more realistic assessment of overall change using this framework. For example, choosing green electricity and reducing energy use in the home will appear to have a greater impact if assessed separately than if combined.

Geographical Detail

As supply chains are increasingly global, using a MRIO database in this method allows for the identification of impacts by source country. In such a case, s can be diagonalized in equation (13), and the indirect impacts aggregated to the country level, with household impacts added to the domestic component.

Temporal Dimension of Interventions

Interventions can focus on affecting the flow of goods and services or the capital stock. The modeling approach taken here, consistent with national accounting conventions, is to look at the annual impact (Hertwich 2011). Hence, we look at the total electricity consumed in a certain year, the total gasoline consumed, the total vehicle manufacture, or the total building construction. The link between stock and flow is obviously more complex than modeled here—certain interventions on flows are only possible under transformation of the existing stock. For example, if we are modeling light-weighting of cars, the reduction of fuel use will only be synonymous with the *new* cars under the intervention, hence the effect would be gradually realized as new cars entered the fleet. The capital service dimension is key to understanding the temporality of emissions reduction (Modaresi et al. 2014).

We abstract from the temporal dimension, however, in order to increase simplicity, transparency and to be consistent with annual accounting both economically and for emissions. Instead, we look at the *potential* reduction of annual flows, given an assumed transformation of the stock. If all cars were light-weighted, this would be the annual emissions reduction due to fuel usage; and this would be the annual emissions reduction/increase due to vehicle construction. A further abstraction occurs from the temporal dimension of the penetration rate t , where behavioral change will not follow immediately from policy intervention. We again look at the potential reduction of a given penetration rate, assuming immediate realization.

An example of the subsequent interpretation of results over the time period of implementation is included in supporting information S1 on the Web.

Case Studies

The intervention-screening method can be linked to any EE I-O database providing the required level of sector detail. The current analysis uses EXIOBASE 3 (Stadler et al. 2018; Wood et al. 2018) (taking year 2011), which provides a high and con-

sistent product resolution (200 products) with a specific focus on environmentally relevant sectors (agriculture, renewable energy, and waste treatment). EXIOBASE provides multiple environmental and social extensions (air and water emissions, land and material inputs, labor). We use total greenhouse gas emissions from all sources except the Intergovernmental Panel on Climate Change (IPCC) category Land Use, Land Use Change and Forestry, and apply IPCC 2007 characterization factors for aggregation of different GHG into carbon dioxide equivalents (CO₂-eq). For further details, we refer to Wood and colleagues (2015). We applied the policy intervention cases to consumption from all EU28 countries and summarized the results of source of impact (where emissions occur) to European Union (EU) and non-EU after the calculation. A full breakdown of country-specific results for each case intervention is included in supporting information S1 on the Web, where the rest of world regions (a small percentage of total impact) are further disaggregated by contribution to regional gross domestic product (GDP).

In the following, we perform two case studies of the policy intervention screening method to assess the environmental performance of different policy and scenario developments in the areas of food and clothing. We select these case studies based on the potential for both demand and supply-chain policy measures. We evaluate the expected reduction in consumption of a list of interventions and compare their carbon-offset potential in the context of the EU. We concentrate on demonstrating the method, rather than conducting an extensive study on technical potentials or penetration rates, which we have estimated based on the available literature. The values selected are upper bounds for potential impact/reduction as estimated by the authors and experts as part of the EU CARBONCAP project on studying the carbon mitigation potential from consumption-based policy.

Case 1: Clothing Sector

The environmental relevance of clothing has increased significantly in the last decades. Clothing contributes approximately 3% of global GHG emissions (Hertwich and Peters 2009). Steen-Olsen and colleagues (2016) demonstrated that in the period from 1999 to 2012, the apparent consumption levels of clothing in Norway roughly tripled to reach an average contribution of 1.2 tonnes CO₂-eq per household in 2012, or 5% of the total household carbon footprint (Steen-Olsen et al. 2016). With all emissions occurring outside the household in the production and distribution stages, there is less accessible knowledge for consumers and policy actors about the importance of impact and their reduction potential.

Intervention 1.1 and 1.2

The intervention modeled encompasses a reduction of the inputs in the production phase, which is equivalent to a reduction of the technical coefficients. This maps the effect of industry changes in the purchase and use of more efficiently produced goods (see table 2, Intervention 1.1 and Intervention 1.2). A

Table 2 Evaluation procedure of environmental interventions

	<i>Intervention examples</i>	<i>Change in A</i>	<i>Change in y</i>	<i>Consumer rebound</i>
	General algorithm	Specify manipulations of the interindustry matrix A (if any) to represent the environmental intervention in question.	Specify manipulations of final demand y (if any) to represent the environmental intervention in question.	Specify if/how the intervention directly leads to monetary savings in y . These savings will lead to rebound effects.
1.1	Buy textiles made of cotton, wool or silk instead of acrylic, polypropylene, PA6, polyester.	10% reduction of the synthetic inputs to the apparel and textile sector leads to increased requirements of plant-based fibers and wool.	—	—
1.2	Buy textiles made of cotton instead of acrylic, polypropylene, PA6, polyester.	10% reduction of the synthetic inputs to the apparel and textile sector leads to increased requirements of plant-based fibers.	—	—
1.3	Reduction in the demand for electricity in the use phase of products, e.g., use energy-efficient washing machines, tumble dryers, and irons	—	5% reduction of electricity demanded by households	Reduced household energy use leads to additional disposable income available for general consumption.
1.4	Reduction in the demand for apparel and textiles, e.g., through extending the life of clothing	—	10% reduction of apparel and textile demanded by households	Reduced household expenditures on clothing leads to additional disposable income available for general consumption.
2.1	Shift toward vegetarian diet	50% reduction in the meat requirements of the hospitality sector, substitution leads to increased requirements of other food products.	50% reduction in the household final demand of meat, substituted by demand for other foods	Substitution of household final demand of meat by cheaper product (assumed 30% of the price) leads to additional disposable income available for household consumption.
2.2	Shift toward low-carbon meats (e.g., chicken/pork instead of beef)		50% reduction in household final demand of carbon-intensive meat, substituted by low-carbon meats	Substitution by cheaper product (assumed 66% of the price) leads to additional disposable income available for household consumption.

Note: Values are upper bounds for potential impact/reduction taken as estimated by the authors and experts as part of the EU CARBONCAP project on studying the carbon mitigation potential from consumption-based policy.

shift of clothing expenditure from synthetic fibers toward natural fibers is an example of an intervention that translates into shifts in the input coefficient structure of the clothing sector in the **A** matrix.

In our simple assessment here, we take 10% of the inputs from the “Rubber and plastics products” sector in the production of clothing and textiles as substituted by inputs of natural fibers; this is assumed to capture the technical potential (30% technically achievable reduction) and uptake rate (33% penetration) combined (see Bartl et al. [2005], Muthu et al. [2012],

and Wang [2010] for justification of parametrization). Intervention 1.1 represents a shift of inputs toward plant-based fibers, wool, and silk, while Intervention 1.2 models a shift toward cotton and other plant-based fibers only.

Intervention 1.3

According to Gardner and Stern (2008), water heating, washing, and drying of clothes contributes to more than 9% of the total energy use and 16% of all in-home energy use of U.S. households. Therefore, interventions aiming for a reduction of

GHG emissions associated with clothing should also target its use phase (Cullen and Allwood 2009), for example, through the encouragement of purchase and use of less energy- and GHG-intensive appliances.

Studies conclude that there is a 5% to 10% reduction in energy demand as households adopt more energy-efficient appliances (Bain et al. 2009; Beton et al. 2014). Measures encouraging a reduction in the number of washes, better loading of the appliances, avoiding tumble drying, or washing at lower temperatures have similar reduction potential (Beton et al. 2014). In order to evaluate the carbon effectiveness of a shift toward more efficient wet appliances, we assume a 5% reduction in the household electricity use (see table 2, Intervention 1.3). This is based on the assumption that wet appliances contribute to 17% of the household energy consumption with energy-efficient wet appliances using up to 30% less energy (DECC 2015; Panzone 2013).

Intervention 1.4

Policies may target a reduction in the demand of clothing itself through increasing the quality and lifetime of products and changing the ways they are disposed of. Beton and colleagues (2014) show that buying more durable garments can increase the lifetime of the clothes between 60% and 90%. Extending the life of clothing through repairs or reusing textiles for a different purpose is expected to result in a significant reduction in the demand of clothing (Buttle et al. 2013). We take a 30% demand reduction to reflect longer lifetimes, and assume a 33% uptake rate, giving a combined effect of 10% reduction (see table 2, Intervention 1.4).

Results

The first two interventions on shifting from synthetic to natural inputs cause only a minuscule reduction in overall emissions, which is due to plant-based fibers and synthetics being rather comparable in terms of their impact per tonne of fiber (Thomas et al. 2012).

The intervention type encouraging more energy-efficient washing machines has the highest emission reduction potential amounting to 11 million tonnes (Mt) CO₂-eq, or 0.3% of the EU's carbon footprint. About 90% of the emissions reduction occurs within the territory of the EU (solid color in figure 1). Finally, reduction in the demand of apparel and textiles results in emission reduction of 3 Mt CO₂-eq and a rebound amounting to 75% of the direct emissions savings. This is due to the relatively low overall carbon intensity of the clothing sector in comparison to all other consumption categories that households shift expenditure to. Breaking down the impact effect in terms of geographical origin suggests that there is actually an increase of emissions within the EU (2.3 Mt CO₂-eq), which is offset by a significant decrease of impacts taking place on non-EU territory (5.3 Mt CO₂-eq) (gradient color in figure 1). A full breakdown of country-specific results for each case study is included in supporting information S1 on the Web, and visualized for the case of textile reduction with the inclusion of rebound case in figure 2. Note that because different products are affected by the

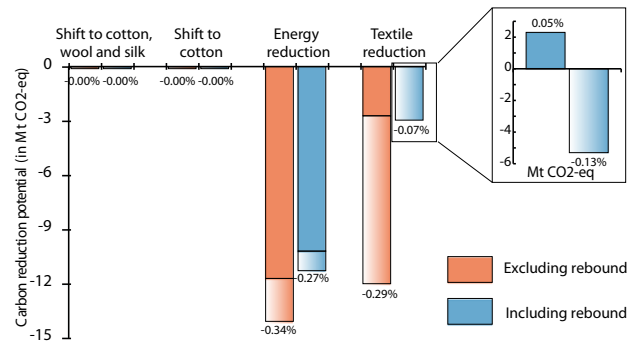


Figure 1 Environmental performance of clothing initiatives excluding/including consumer rebound effect. The anticipated reduction of the total European Union (EU) carbon footprint is measured in Mt CO₂-eq savings distinguishing between emissions occurring on the territory of EU (solid color) and non-EU countries (gradient). The percentages indicate relative savings compared to the total EU carbon footprint. Mt CO₂-eq = million tonnes of carbon dioxide equivalents.

intervention, versus products affected by the rebound, we are able to show geographically disperse results where the intervention is likely to lead to increased pollution in some countries, compared to reduced pollution in other countries and overall.

Case study 2: Food and Diets

Food consumption is an important contributor to the overall carbon footprint of developed countries (Hertwich and Peters 2009). One class of climate interventions targets consumer behavior, with the aim of changing consumption patterns. This includes a shift from meat to vegetarian diet (including purchased meals in restaurants) as well as an increase of home cooking (eating out less frequently). Alternatively, interventions can be targeted at the business side of hospitality services (which includes hotels and restaurants). Taken together, the hospitality industry represents 3.7% of the European GDP and 7.8% of employment (Ernst & Young 2013). A number of climate policy initiatives can be directed at the hospitality sector. One class of interventions concern efforts to green the supply chain of an industry, which can come about from shifts in the supply chain where some system inputs are substituted either by alternative suppliers of the same product, or by a shift to alternative product inputs with similar function but lower supply-chain emission intensities.

Intervention 2.1

First, we evaluate the ambitious case of a large-scale shift away from meat toward vegetarian alternatives, including restaurant meals as well as food cooked in households. We define this as a 50% reduction in overall meat consumption (100% technically possible meat reduction, penetration rate 50%). We model this as a change in both the technical coefficients matrix (**A**) and the household consumption matrix (**y**).

Specifically, the hospitality sectors' input requirements from the various meat products sectors were reduced, while we assumed a corresponding increase in its demands on the sectors delivering vegetables, fruits, grains, and other nonmeat food products. The household consumption matrix (y) was modified analogously.

In this case, we make use of the method's option to deflate the shift in input. This mechanism allows us to define an estimated coefficient to adjust input shifts in the case where the price of the substituted input can be expected to be significantly different from the original. Since meat is, on average, more expensive than the substitute products, a complete shift in monetary terms would overestimate the required inputs in volume terms. We assume here that the inputs from the fruit and vegetable sectors are increased by 30% of the reduction in meat inputs (upper bound of change, as estimated by the authors). For the adjustments of final demand, the rebound effect was modeled by redistributing the savings based on marginal consumption in all other categories (see table 2, Intervention 2.1).

Intervention 2.2

In this intervention, we evaluate a shift in household food purchases away from beef toward less carbon-intensive meats (pork and poultry) corresponding to 50% of the current demand of carbon-intensive beef products. Again, we apply the shift deflation option, here assuming the commodity price to be 33% lower on average for the low-carbon meat types (see table 2, Intervention 2.2).

Results

The hypothetical reduction of meat consumption by Europeans directly resulted in a decrease in global emissions of about 140 Mt CO₂-eq, corresponding to 3.3% of the European carbon footprint (figure 3). This is in line with Berners-Lee and colleagues (2012), who took a bottom-up approach to estimate that a complete shift (i.e., assuming 100% penetration rate) to veg-

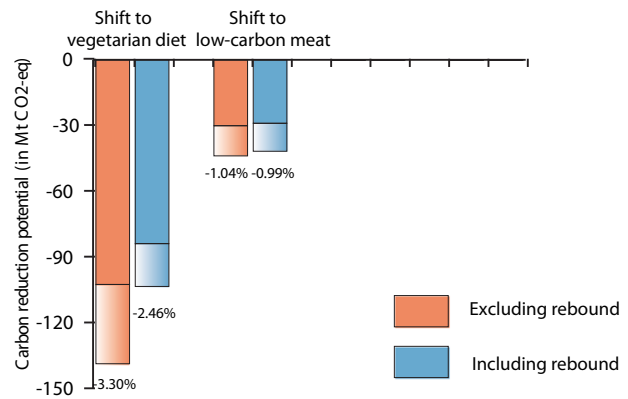


Figure 3 Environmental performance of food and diets initiatives excluding/including consumer rebound effect. The anticipated reduction of the total European Union (EU) carbon footprint is measured in Mt CO₂-eq savings distinguishing between emissions occurring on the territory of EU (solid color) and non-EU countries (gradient). The percentages indicate relative savings compared to the total EU carbon footprint. Mt CO₂-eq = million tonnes of carbon dioxide equivalents.

etarian diets in the UK could reduce the total carbon footprint of the UK by 4.8%. After accounting for rebounds including increased demand of non-meat food products as well as increased general consumption due to the resulting reduced food expenditures overall, the estimate for achievable emission reductions was reduced to 103 Mt CO₂-eq (2.5%). In other words, the rebound effect of this intervention, consisting of emissions associated with increased general consumption due to consumer savings from the reduced meat expenditures, amount to 25% of the direct emissions savings. Scott and colleagues (2009) assessed a reduction in within-household meat consumption in the UK of 50% by 2050, and found a reduction in the total UK carbon footprint by 1.6% compared to the baseline, excluding rebound effects. Most emissions reductions in our analysis occur in the EU (81%), whereas emission reduction in non-EU

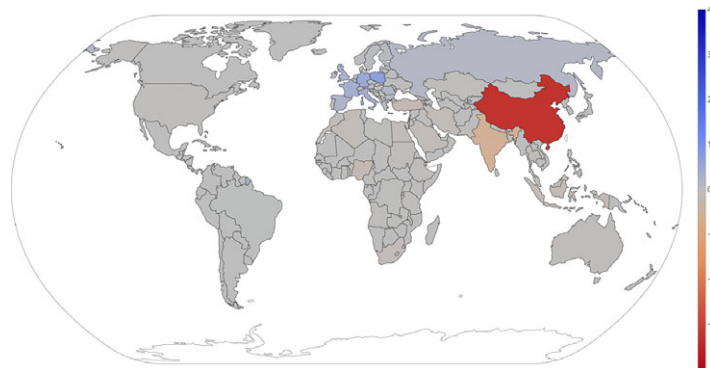


Figure 2 Estimates of geographical effects of switching the clothing initiative (reduction of textiles) in the European Union (EU) including consumer rebound effect. The anticipated impact on the EU carbon footprint is measured in Mt CO₂-eq with blue showing reductions and red showing increases due to rebound for increased consumption of products sourced from those countries. Note: Trade shares are assumed static, and net impact only is shown. Mt CO₂-eq = million tonnes of carbon dioxide equivalents.

countries is mainly due to feed inputs. These results are included at the country level in supporting information S1 on the Web.

For the alternative, less drastic, case of rather shifting household purchases from higher to lower carbon-intensive meats, the reduction is less pronounced. The direct emission reduction associated with the reduced purchase of red meats amounts to 44 Mt CO₂-eq. In contrast to the vegetarian example discussed previously, however, after redistributing the expenditures on white meat and on general consumption, the net savings were in this case still estimated to be 42 Mt CO₂-eq, corresponding to a rebound of only 5% of the gross emission reductions. The relatively low rebound effect observed in this case represents a shift from one product to another that fulfils the same function at a lower carbon intensity of production, yet at a price to consumers that is not very different from that of the original product. These results broadly agree with previous, more detailed work on dietary change that found that an EU-wide shift toward a lower-meat “Mediterranean” diet could result in 0.5% to 1.5% reduction in the EU’s footprint and a significant decrease in land use (Tukker et al. 2011; Stehfest et al. 2009). About 70% of emission reduction takes place within the EU.

Discussion

This paper describes a framework to estimate the climate-change mitigation potential of a wide range of consumption-oriented policy measures. While the approach is intentionally not as detailed as bottom-up studies of individual measures, it is able to provide a quicker assessment utilizing already available data in MRIO tables and thus requiring less intervention-specific data. The framework allows assessing integrated policies for reducing GHGs that combine changing consumption patterns with changes in the composition or manufacturing of the products demanded. The modeling can be based on any detailed IOT and, if multi-regional, can describe the impact across the global economy, thus reflecting the actual geographical distribution and emissions factors of global production networks.

By incorporating exogenous technological and demand change, alongside price effects, we model direct and indirect effects of interventions (including product substitution), but not the price effects or micro-level detail. The framework purposely does not model systemic rebound effects (i.e., macro-economic price or growth effects [Gillingham et al. 2013]). While this is one (intentional) limitation of the framework, it allows for a clearer understanding of the cause/effect mechanisms of individual interventions and should be seen as complementary to, rather than an alternative to, dynamic modeling.

We present two case studies—interventions of the clothing and diets sector—in order to highlight the potential of the framework to assess interventions targeting both consumer demand and production. We find potentially limited carbon footprint reductions to be achieved in the interventions

investigated in the supply chain of clothing production and more in targeting consumer behavior, and find significant savings, with only moderate rebound, in the example of diet change policy. We focus here on climate policy, but the methods are readily generalizable to investigate the impacts on other environmental pressures included in available EE-MRIO tables (such as land use and water use). Such generalization can then give important insights into the potential “problem-shifting” of each policy measure.

The approach presented here has a range of pros and cons in comparison to other methods. In comparison to technology-focused/LCA work, the method can provide much quicker estimates for prioritization of the many policy interventions and lifestyle options across disparate sectors and product groups by making use of extensive macro-level data sets. Furthermore, because all intervention options are assessed in a common modeling framework, the assessments of various policies are more easily comparable and can be applied simultaneously to take into account interaction effects among them. Such interaction effects become large when multiple interventions are applied simultaneously as would be required to meet stringent climate policy targets, and it is nigh impossible to capture such effects without a single integrated approach. However, the approach is only as precise on capturing direct effects as the parametrization performed—interventions on specific changes must be integrated in generally aggregate product groups used in IOA. Furthermore, without extending to endogenizing capital and treating stock cohorts, the method can only capture longer-term trends and not spikes in the turnover of capital stock. Many dynamic models (macro-econometric, dynamic I-O, dynamic computational general equilibrium, or integrated assessment models) attempt to capture such dynamics, but are often limited in sectoral resolution and highly dependent on assumptions of substitutability of inputs and parametrization on price elasticities. Furthermore, the approach will not capture highly nonlinear responses to a policy intervention (e.g., economies of scale, capital lock-in), or the inhomogeneity of consumer units. However the approach is well suited to assess a broad suite of measures, and offers the opportunity to assess the direct and supply-chain contribution of a “behavioral wedge” of climate-change mitigation options.

Acknowledgments

We thank João Rodrigues for discussion around methods and the anonymous reviewers for their constructive comments on earlier versions of the manuscript.

Funding Information

This work was supported by the EU’s 7th Framework Program under grant agreement No. 308552 (DESIRE), No. 603386 (CarbonCAP), and No 613420 (GLAMURS), the Norwegian Research Council Grants No. 233698 (Karbonfotspor), and No. 235462 (People’s climate research).

References

- Bain, J., A. Beton, A. Schultze, S. Mudgal, M. Dowling, R. Holdway, and J. Owens. 2009. *Reducing the environmental impact of clothes cleaning*. EV0419. Final Report to the Department for Environment, Food and Rural Affairs. London: Department for Environment, Food and Rural Affairs.
- Baiocchi, G., J. Minx, and K. Hubacek. 2010. The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom. *Journal of Industrial Ecology* 14(1): 50–72.
- Barker, T., A. Dagoumas, and J. Rubin. 2009. The macroeconomic rebound effect and the world economy. *Energy Efficiency* 2(4): 411–427.
- Baroni, L., L. Cenci, M. Tettamanti, and M. Berati. 2007. Evaluating the environmental impact of various dietary patterns combined with different food production systems. *European Journal of Clinical Nutrition* 61(2): 279–286.
- Barrett, J. and K. Scott. 2012. Link between climate change mitigation and resource efficiency: A UK case study. *Global Environmental Change* 22(1): 299–307.
- Bartl, A., A. Hackl, B. Mihalyi, M. Wistuba, and I. Marini. 2005. Recycling of fibre materials. *Process Safety and Environmental Protection* 83(4): 351–358.
- Berners-Lee, M., C. Hoolohan, H. Cammack, and C. N. Hewitt. 2012. The relative greenhouse gas impacts of realistic dietary choices. *Energy Policy* 43: 184–190.
- Beton, A., D. Dias, L. Farrant, T. Gibon, Y. L. Guern, M. Desaxce, A. Perwuelz, and I. Boufateh. 2014. *Environmental Improvement Potential of textiles (IMPRO Textiles)*, EUR Number: 26316 EN. <http://ipts.jrc.ec.europa.eu/publications/pub.cfm?id=6960>. Accessed 20 October 2017.
- Borken-Kleefeld, J., J. Fuglestvedt, and T. Berntsen. 2013. Mode, load, and specific climate impact from passenger trips. *Environmental Science & Technology* 47(14): 7608–7614.
- Buttle, M., D. Vyas, and C. Spinks. 2013. Evaluating the financial viability and resource implications for new business models in the clothing sector. Project code: RNF100-005. Oxon, UK: Waste and Resources Action Programme (WRAP).
- Chester, M. V. and A. Horvath. 2009. Environmental assessment of passenger transportation should include infrastructure and supply chains. *Environmental Research Letters* 4(2): 024008.
- Cullen, J. M. and J. M. Allwood. 2009. The role of washing machines in life cycle assessment studies. *Journal of Industrial Ecology* 13(1): 27–37.
- DECC (Department Of Energy & Climate Change). 2015. *Energy consumption in the UK (2015)*. <http://webarchive.nationalarchives.gov.uk/20160510033717/https://www.gov.uk/government/statistics/energy-consumption-in-the-uk>. Accessed 20 October 2017.
- Dietz, T., G. T. Gardner, J. Gilligan, P. C. Stern, and M. P. Vandenberg. 2009. Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences of the United States of America* 106(44): 18452–18456.
- Dixon, P. B. and D. W. Jorgenson. 2013. Chapter 1—Introduction. In *Handbook of computable general equilibrium modeling*, edited by B. D. Peter and W. J. Dale. Amsterdam: Elsevier.
- Ernst & Young. 2013. *The hospitality sector in Europe*. London: Ernst & Young.
- Eurostat. 2008. *Eurostat manual of supply, use and input-output tables*. Luxembourg: European Commission.
- Finkbeiner, M. 2009. Carbon footprinting—Opportunities and threats. *The International Journal of Life Cycle Assessment* 14(2): 91–94.
- Font Vivanco, D. and E. van der Voet. 2014. The rebound effect through industrial ecology's eyes: A review of LCA-based studies. *The International Journal of Life Cycle Assessment* 19(12): 1933–1947.
- Font Vivanco, D., J. Freire-González, R. Kemp, and E. van der Voet. 2014. The remarkable environmental rebound effect of electric cars: A microeconomic approach. *Environmental Science & Technology* 48(20): 12063–12072.
- Gardner, G. T. and P. C. Stern. 2008. The short list—The most effective actions US households can take to curb climate change. *Environment* 50(5): 12–24.
- Gibon, T., R. Wood, A. Arvesen, J. D. Bergesen, S. Suh, and E. G. Hertwich. 2015. A methodology for integrated, multiregional life cycle assessment scenarios under large-scale technological change. *Environmental Science & Technology* 49(18): 11218–11226.
- Gillingham, K., M. J. Kotchen, D. S. Rapson, and G. Wagner. 2013. Energy policy: The rebound effect is overplayed. *Nature* 493(7433): 475–476.
- Girod, B. and P. de Haan. 2009. GHG reduction potential of changes in consumption patterns and higher quality levels: Evidence from Swiss household consumption survey. *Energy Policy* 37(12): 5650–5661.
- Girod, B., D. P. V. Vuuren, and E. G. Hertwich. 2014. Climate policy through changing consumption choices: Options and obstacles for reducing GHG emissions. *Global Environmental Change* 25: 5–15.
- Grabs, J. 2015. The rebound effects of switching to vegetarianism. A microeconomic analysis of Swedish consumption behavior. *Ecological Economics* 116: 270–279.
- Haue, M. O. 2006. *Income elasticity and economic development: Methods and applications*. New York: Springer.
- Hertwich, E. and G. Peters. 2009. Carbon footprint of nations: A global, trade-linked analysis. *Environmental Science & Technology* 43(16): 6414–6420.
- Hertwich, E. G. 2005. Consumption & the rebound effect: An industrial ecology perspective. *Journal of Industrial Ecology* 9(1–2): 85–98.
- Hertwich, E. G. 2011. The life cycle environmental impacts of consumption. *Economic Systems Research* 23(1): 27–47.
- 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.
- Jones, C. and D. M. Kammen. 2014. Spatial distribution of U.S. household carbon footprints reveals suburbanisation undermines greenhouse gas benefits of urban population density. *Environmental Science & Technology* 48(2): 895–902.
- Jones, C. M. and D. M. Kammen. 2011. Quantifying carbon footprint reduction opportunities for U.S. households and communities. *Environmental Science & Technology* 45(9): 4088–4095.
- Lenzen, M. and C. J. Dey. 2002. Economic, energy and emissions impacts of some environmentally motivated consumer, technology and government spending options. *Energy Economics* 24: 377–403.
- Lenzen, M. and R. Crawford. 2009. The path exchange method for hybrid LCA. *Environmental Science & Technology* 43(21): 8251–8256.
- Leontief, W. 1970. Environmental repercussions and the economic structure: An input-output approach. *Review of Economics and Statistics* 52(3): 262–271.

- Majeau-Bettez, G., R. Wood, and A. H. Strømman. 2014. Unified theory of allocations and constructs in life cycle assessment and input-output analysis. *Journal of Industrial Ecology* 18(5): 747–770.
- Majeau-Bettez, G., R. Wood, E. G. Hertwich, and A. H. Strømman. 2016. When do allocations and constructs respect material, energy, financial, and production balances in LCA and EEIO? *Journal of Industrial Ecology* 20(1): 67–84.
- Malik, A., M. Lenzen, R. N. Ely, and E. Dietzenbacher. 2014. Simulating the impact of new industries on the economy: The case of biorefining in Australia. *Ecological Economics* 107: 84–93.
- Meier, T. and O. Christen. 2013. Environmental impacts of dietary recommendations and dietary styles: Germany as an example. *Environmental Science & Technology* 47(2): 877–888.
- Minx, J. C., T. Wiedmann, R. Wood, G. P. Peters, M. Lenzen, A. Owen, K. Scott, et al. 2009. Input-output analysis and carbon footprinting: An overview of applications. *Economic Systems Research* 21(3): 187–216.
- Modaresi, R., S. Pauliuk, A. N. Løvik, and D. B. Müller. 2014. Global carbon benefits of material substitution in passenger cars until 2050 and the impact on the steel and aluminum industries. *Environmental Science & Technology* 48(18): 10776–10784.
- Munksgaard, J., M. Wier, M. Lenzen, and C. Dey. 2005. Using input-output analysis to measure the environmental pressure of consumption at different spatial levels. *Journal of Industrial Ecology* 9(1–2): 169–185.
- Murray, C. K. 2013. What if consumers decided to all ‘go green’? Environmental rebound effects from consumption decisions. *Energy Policy* 54: 240–256.
- Muthu, S. S., Y. Li, J. Y. Hu, and P. Y. Mok. 2012. Quantification of environmental impact and ecological sustainability for textile fibres. *Ecological Indicators* 13(1): 66–74.
- NEEDS (New Energy Externalities Developments for Sustainability). 2009. New Energy Externalities Developments for Sustainability. www.needs-project.org. Accessed 20 October 2017.
- O’Rourke, D. 2014. The science of sustainable supply chains. *Science* 344(6188): 1124–1127.
- Panzone, L. A. 2013. Saving money vs investing money: Do energy ratings influence consumer demand for energy efficient goods? *Energy Economics* 38: 51–63.
- Pfaff, M. and C. Sartorius. 2015. Economy-wide rebound effects for non-energetic raw materials. *Ecological Economics* 118: 132–139.
- Rose, A. 1984. Technological change and input-output analysis: An appraisal. *Socio-Economic Planning Sciences* 18: 305–318.
- Schanes, K., S. Giljum, and E. Hertwich. 2016. Low carbon lifestyles: A framework to structure consumption strategies and options to reduce carbon footprints. *Journal of Cleaner Production* 139: 1033–1043.
- Scott, K., J. Barrett, G. Baiocchi, and J. Minx. 2009. Meeting the UK climate change challenge: The contribution of resource efficiency. Report to the Waste and Resources Action Programme, York, UK.
- Sorrell, S. 2009. Jevons’ Paradox revisited: The evidence for backfire from improved energy efficiency. *Energy Policy* 37(4): 1456–1469.
- Stadler, K., R. Wood, T. Bulavskaya, C.-J. Södersten, M. Simas, S. Schmidt, A. Usubiaga, et al. 2018. EXIOBASE3: Developing a time series of detailed Environmentally Extended Multi-Regional Input-Output tables. *Journal of Industrial Ecology* 22(3): 502–515.
- Steen-Olsen, K. and E. G. Hertwich. 2014. Life cycle assessment as a means to identify the most effective action for sustainable consumption. In *Handbook of research on sustainable consumption*, edited by L. Reisch and J. Thøgersen. Glos, UK: Edward Elgar.
- 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.
- Stehfest, E., L. Bouwman, D. van Vuuren, M. J. den Elzen, B. Eickhout, and P. Kabat. 2009. Climate benefits of changing diet. *Climatic Change* 95(1–2): 83–102.
- Takase, K., Y. Kondo, and A. Washizu. 2005. An analysis of sustainable consumption by the waste input-output model. *Journal of Industrial Ecology* 9(1–2): 201–219.
- Thomas, B., M. Fishwick, J. Joyce, and A. van Santen. 2012. A carbon footprint for UK clothing and opportunities for savings. www.wrap.org.uk/sites/files/wrap/Appendix IV - Carbon footprint report.pdf. Accessed 20 October 2017.
- Tisserant, A., R. Wood, D. Ivanova, and G. Vita. 2017. Forecasting consumption: The income effect on future emission scenarios. *Journal of Industrial Ecology* Forthcoming.
- Tukker, A., A. de Koning, R. Wood, S. Moll, and M. Bouwmeester. 2013. Price corrected domestic technology assumption—A method to assess pollution embodied in trade using primary official statistics only. With a case on CO₂ emissions embodied in imports to Europe. *Environmental Science & Technology* 47(4): 1775–1783.
- Tukker, A., R. A. Goldbohm, A. de Koning, M. Verheijden, R. Kleijn, O. Wolf, I. Pérez-Domínguez, and J. M. Rueda-Cantuche. 2011. Environmental impacts of changes to healthier diets in Europe. *Ecological Economics* 70(10): 1776–1788.
- Wang, Y. 2010. Fiber and textile waste utilization. *Waste and Biomass Valorization* 1(1): 135–143.
- Weber, C. L. and H. S. Matthews. 2008. Quantifying the global and distributional aspects of American household carbon footprint. *Ecological Economics* 66(2–3): 379–391.
- Weidema, B. P., M. Thrane, P. Christensen, J. Schmidt, and S. Løkke. 2008. Carbon footprint. A catalyst for life cycle assessment? *Journal of Industrial Ecology* 12(1): 3–6.
- West, G. R. 1995. Comparison of input-output, input-output + econometric and computable general equilibrium impact models at the regional level. *Economic Systems Research* 7(2): 209–227.
- West, S. E., A. Owen, K. Axelsson, and C. D. West. 2016. Evaluating the use of a carbon footprint calculator: Communicating impacts of consumption at household level and exploring mitigation options. *Journal of Industrial Ecology* 20(3): 396–409.
- Wilting, H. C., A. Faber, and A. M. Idenburg. 2008. Investigating new technologies in a scenario context: Description and application of an input-output method. *Journal of Cleaner Production* 16(s1): S102–S112.
- Wood, R. and C. Dey. 2009. Australia’s carbon footprint. *Economic Systems Research* 21(3): 243–266.
- Wood, R., T. R. Hawkins, E. G. Hertwich, and A. Tukker. 2014. Harmonising national input-output tables for consumption-based accounting—Experiences from EXIOPOL. *Economic Systems Research* 26(4): 387–409.
- Wood, R., K. Stadler, T. Bulavskaya, S. Lutter, S. Giljum, A. de Koning, J. Kuonen, et al. 2015. Global sustainability accounting—developing EXIOBASE for multi-regional footprint analysis. *Sustainability (Switzerland)* 7(1): 138–163.
- Wood, R., K. Stadler, M. Simas, T. Bulavskaya, S. Giljum, S. Lutter and A. Tukker. 2018. Growth in environmental footprints and environmental impacts embodied in trade: Resource efficiency indicators from EXIOBASE3. *Journal of Industrial Ecology* 22(3): 553–564.

Supporting Information

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

Supporting Information S1: This supporting information contains a simplified representation of input data into interventions. Additionally, functionality can be added/removed depending on the level of automation desired. The crux of interaction with the MRIO system is the product and sector concordance—which can be done in many ways, but a “light” version is included here. Data files are provided online at <https://figshare.com/s/ab87776ce825f6c53c27>.