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Future changes in consumption: The income effect on greenhouse gas emissions

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ABSTRACT

The scale and patterns of household consumption are important determinants of environmental impacts. Whilst affluence has been shown to have a strong correlation with environmental impact, they do not necessarily grow at the same rate. Given the apparent contradiction between the sustainable development goals of economic growth and environmental protection, it is important to understand the effect of rising affluence and concurrent changing consumption patterns on future environmental impacts. Here we develop an econometric demand model based on the data available from a global multiregional input-output dataset. We model future household consumption following scenarios of population and GDP growth for 49 individual regions. The greenhouse gas (GHG) emissions resulting from the future household demand is then explored both with and without consideration of the change in expenditure over time on different consumption categories. Compared to a baseline scenario where final demand grows in line with the 2011 average consumption pattern up until 2030, we find that changing consumer preferences with increasing affluence has a small negative effect on global cumulative GHG emissions. The differences are more profound on both a regional and a product level. For the demand model scenario, we find the largest decrease in GHG emissions for the BRICS and other developing countries, while emissions in North America and the EU remain unchanged. Decreased spending and resulting emissions on food are cancelled out by increased spending and emissions on transportation. Despite relatively small global differences between the scenarios, the regional and sectoral wedges indicate that there is a large untapped potential in environmental policies and lifestyle changes that can complement the technological transition towards a low-emitting society.

1. Introduction

Households in particularly wealthy countries are causing environmental pressures due to their high demand for goods and services. Globally, households represent about two-thirds of the demand for raw materials and land as well as the waste flows mobilized by production activities, and their attendant environmental loads (Munksgaard et al., 2000, Weber and Matthews, 2008, Steinberger and Roberts 2010, Ivanova et al., 2016). Technology improvements and changes in production are expected to play vital roles in mitigating climate change, but an increasing number of studies suggest that avoiding environmental degradation will not be possible without significant contributions from the consumption side (van Sluisveld et al., 2016, Dietz et al., 2009, Creutzig et al., 2018, Intergovernmental Panel on Climate Change, 2019). Sustainable consumption is part of the UN Sustainable Development Goals (SDG12[1]) and can be achieved by either shifting

Abbreviations: ABM, Agent-based modelling; AIDS, Almost ideal demand system; BRICS, Brazil, Russia, India, China and South Africa; CES, Consumer expenditure survey; CF, Carbon footprint; GHG, Greenhouse gas; GME, Generalized maximum entropy; IIA, Information inaccuracy; MRIO, Multiregional input-output; PADS, Perhaps adequate demand system; QUAIDS, Quadratic Almost ideal demand system; RMSE, Root mean squared error; RoW, Rest-of-the-world.

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[1] http://www.un.org/sustainabledevelopment/sustainable-consumption-production/

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the pattern of consumption or lowering total consumption. Several studies suggest that there is a large untapped potential for climate change mitigation in consumption side changes (Dietz et al., 2009, Girod et al., 2014, Vita et al., 2019, Lekve Bjelle et al., 2018, Wynes and Nicholas, 2017, Moran et al., 2018) and that some policies aimed at consumer choices have the benefit of low implementation costs (Allcott and Mullainathan 2010).

Due to the ability to allocate indirect environmental impacts to the final consumption activities they serve, environmental extended multi-regional input-output (MRIO) models are useful for ranking types of consumption in terms of total environmental impacts, thus potentially allowing prioritization of areas with the greatest improvement potential with respect to sustainable consumption (Lorek and Spangenberg, 2001, Tukker et al., 2006). In addition to the common carbon footprint, MRIO models are being applied to study a wide range of other environmental impacts, such as smog formation, acidification and eutrophication (Kerkhof et al., 2009b, Hamilton et al., 2018), material use (Muñoz et al., 2009, Bruckner et al., 2012), water use (Mekonnen and Hoekstra, 2012), land use (Ivanova et al., 2016), solid waste (Tisserant et al., 2017) and the Ecological Footprint (Wiedmann et al., 2006).

There are several cross-sectional studies that investigate the relationship between income and demand for products and the associated environmental impact of consumption for a single country and year (Wier et al., 2001, Weber and Matthews, 2008, Kerkhof et al., 2009b, Duarte et al., 2010, Steen-Olsen et al., 2016). Kerkhof et al. (2009a) find that for the UK and the Netherlands, per capita GHG emission is higher than for Sweden and Norway. However, the GHG intensity of consumption decreases with increasing affluence in the Netherlands and the UK but grow in Sweden and Norway. Levinson and O'Brien (2015) found that richer households in the US are responsible for more pollution, but with an income elasticity of less than one. They conclude that the observation of decreasing pollution per dollar of expenditure with rising income comes from both lower consumption per additional dollar earned and the fact that households consume goods that pollute less in 2012 than 1984. In a cross-country analysis, Hertwich and Peters (2009) show that services have the highest expenditure elasticity, while having one of the lowest GHG emission elasticities. This indicates that changes in consumption patterns are important to consider for rebound type calculations which concern the environmental implications of re-spending of savings from either technological improvements or reduced consumption on particular goods (Lekve Bjelle et al., 2018, Thiesen et al., 2008, Tukker et al., 2013).

1.1. Towards combined MRIO-demand systems

Growing affluence brings about both increases in consumption and changes in consumption patterns, as spending does not increase uniformly across all products. This effect was first noticed by Engel in 1895 who observed that the share of expenditure on food decreases with increasing income in a given population (Engel's Law) (Engel 1895, Chakrabarty and Hildenbrand 2016). The relationship between changes in consumption patterns with changing income are typically shown using income elasticities or Engel curves. The income elasticity measures the percentage change in demand given a change in income and correspond to linear Engel curves that graphically show the relationship between levels of demand and income. The existence of linear Engel curves across all goods and services is highly unlikely (Blundell and Ray, 1984, Banks et al., 1997), particularly for cross-sectional data (Blundell and Ray, 1984) and implies that goods are not permitted to be luxuries at some income levels and and necessities at others (Banks et al., 1997).

In the 1950s and onwards came models of complete demand systems that describe consumer behavior by specifying both Engel curves and effects of changes in prices consistent with utility maximization (Banks et al., 1997) and represent the decision process faced by a rational representative consumer (Deaton and Muellbauer, 1980). Some of the most prominent models are the Linear Expenditure System (Stone 1954), the Quadratic Demand System (Pollak and Wales, 1978), the Almost Ideal Demand System (Deaton and Muellbauer, 1980), the Quadratic Almost Ideal Demand System (Banks et al., 1997) and the Perhaps Adequate Demand System (PADS) (Almon 1998).

Implementation of demand systems in micro-economic analysis is now common, and they are also used in macro-economic models that consider technological change in the economy integrated with changes in consumption, investments and government expenditure (e.g. Sommer and Kratena, 2017). Several macro-econometric input-output models that estimate environmental impacts under different scenarios exist today, such as E3ME (Barker 1999), GINFORS (Lutz et al., 2009, Distelkamp and Meyer, 2019, Meyer and Ahlert, 2019, Wiebe 2016) and the World Trade Model combined with MRIO (Duchin and Levine 2016). These models focus on the impact of future changes in trade patterns, technology, future impacts under different scenarios of taxations, or a top-down approach where they investigate how future emission targets can be met. Importantly, they are able to include the modelling of macro-economic feedbacks (price effects, economies of scale, etc.) between producers and consumers, however, it then becomes difficult to isolate the impact of specific agents (such as households), due to the endogeneity of modelled change.

Using, such approaches, Kim et al. (2015) studied the impact of future changes in demographic variables (income and age) on consumption patterns, but only for a single region and without considering associated environmental impact. They did this by integrating an almost ideal demand system (AIDS) model based on consumer expenditure survey (CES) data into a regional input-output model. Mongelli et al. (2010) used data from a CES to compute their AIDS model to model sustainable consumption. Their motivation was to extend IO models with a more accurate representation of household demand to study the response of household consumption to policy interventions. Although their paper focuses on the methodological linking between IO databases and CES data, they include a scenario on the emission effects of a CO_2 tax levied on industries. After running the IO calculations, the consumers are then faced with a price change and a change in final expenditure which are modelled using the demand system. In a slightly different vein of research, but ignoring endogenous feedbacks, Wiebe et al. (2018) estimate climate change scenarios in a forward-looking version of EXIOBASE, where future consumption changes were estimated by the use of a demand system, in addition to including scenarios of future technological changes that were determined by exogenous estimates of change.

None of these approaches, however, isolate the effect that future growth in income will have on changing consumption patterns and associated carbon footprints. The work of Sommer and Kratena (2017) probably comes closest, but it focuses on the cross-sectional distribution (by quintile) and related carbon footprints for Europe. Hence in order to better understand the relation between the dynamics of household demand and embodied emissions at the global scale, we link a demand system model with multiregional input-output data. We use this to estimate the effect of increasing income on changes in consumption patterns for 49 regions from the EXIOBASE dataset (Section 2). We then compare the GHG emissions of two scenarios of future consumption (Section 3). The scenarios are driven by increasing affluence and population but differ in the way demand for goods and services grows. The 'static' scenario distributes expenditures according to the 2011 products' share of expenditure, while the Quadratic Almost Ideal Demand System (QUAIDS) scenario uses regression results to forecast demand for products. We calculate the direct and indirect GHG emissions associated with household consumption assuming 2011-constant emission multipliers and constant economic structure, thus isolating the effect of shifting consumption patterns. We supply a framework for global comparison of the effect of affluence on environmental impacts that can be used as a guide to policy makers to lower future emissions from household consumption and provides possibilities for analyses beyond what is explored in this paper. We aim at increased understanding of how changed affluence may affect future emissions globally.

2. Methods

2.1. EXIOBASE database

EXIOBASE is an MRIO database with environmental and socioeconomic extensions. Version 3 of the database used in this article consists of 44 countries and 5 rest-of-the-world (RoW) regions at a level of 163 industries and 200 products. EXIOBASE 3 provides a time series of MRSUT from 1995 to 2011, from which symmetric product-by-product MRIO tables are formed. For a more detailed description of the database and its sources we refer the reader to Wood et al. (2015), and Stadler et al. (2018). GHG emissions available in EXIOBASE allocated to industrial sector and final products were used in this work, covering six major greenhouse gases (CO_2, CH_4, N_2O, SF_6, HFCs and PFCs), and using the IPCC, 2007 Global Warming Potential (GWP) 100 metric.

Total household consumption data in basic pricing was retrieved from the household consumption vector in EXIOBASE 3, including both imported and domestically demanded goods. The current price household expenditure data was first aggregated by collapsing imported and domestically consumed goods. Next, the expenditure data was deflated using the product-level deflators described in Stadler et al. (2018) with base year in 2011. Both the current price expenditure data and the deflated expenditure data were then aggregated to the 15 product groups of the demand system, and price indices were estimated as the current price expenditure divided by the deflated expenditure. Expenditure shares were extracted from the current price expenditure data.

As EXIOBASE has a high product resolution of 200 products, there are products with no household consumption, in some or all regions of the database. Particularly, we found only 42 sectors in EXIOBASE 3 with non-zero household expenditure data for all years and regions. Zero expenditure can cause problems in the estimations of demand systems (Blundell and Robin 1999, Bardazzi and Barnabani, 2001). When projecting demand, such low or zero expenditures can cause unrealistic shifts in consumption patterns. These shifts can be amplified for emissions if observed for product groups with particularly high carbon intensities per monetary unit. Hence, we performed the analysis at a level of 15 product groups (see S1 for the product concordance), after several iterations of the product aggregations to avoid low expenditure shares and unrealistic projected expenditure due to large jumps in historic sectoral data. We set the lower limit for historic expenditure shares at 0.3% to avoid the mentioned problems caused by low shares. Our product resolution is at the upper end of what we found in the demand system literature.

2.2. Estimating demand systems

Demand systems estimate absolute values of consumption (e.g. PADS) or household budget shares (e.g. AIDS) through prices of goods, household income and a price index. Some models also include some form of time trend (e.g. PADS) or a quadratic income term (e.g. QUAIDS). These models are often expanded with demographic variables such age or household size. Different constraints from demand theory are put on the parameters. In the most widely used demand system, AIDS (Deaton and Muellbauer, 1980), these include the adding up constraint (the sum of all budget shares add up to one), homogeneity of degree zero in prices and total expenditure taken together, and Slutsky symmetry.

We estimate the Quadratic Almost Ideal Demand System due to its ability to allow for non-linear Engel curves through a quadratic income term. Non-linear Engel curves have been proven to exist for certain commodities (Banks et al., 1997). They allow the representation of goods as luxuries or necessities at different expenditure levels. We choose the QUAIDS model given our large range of income levels, and our focus on the changing nature of consumption in comparison to income for a range of carbon intensive goods such as transport, food and housing, which can be seen as both necessities and luxuries at different income levels. In S11 we plot Engel curves for selected key regions. Non-linear curves can be observed across several of the product groups, and particularly for "restaurants and hotels", "clothing", "tobacco and beverages", and the housing and food product groups. In addition to the quadratic income term, we include country-specific intercepts. The number of observations per product group in the demand system is yearly data (17 years) for the 49 regions of EXIOBASE.

The QUAIDS specification is given by:

$$w_{itc} = \alpha_{ic} + \sum_{j=1}^{n} \zeta_{ij} \ln p_{jtc} + \beta_i \ln\left(\frac{Y_{tc}}{P_{tc}}\right) + \frac{\gamma_i}{\prod_{j=1}^{n} p_{jtc}^{\beta_j}} * \lfloor ln\left(\frac{Y_{tc}}{P_{tc}}\right)\rfloor^2 + \varepsilon_{itc} \quad (1)$$

The notation is as follows:

- i, j (Product groups)
- n (Number of product groups)
- c (Country index)
- t (Time index)
- P (Stone price index)
- $\alpha, \gamma, \beta, \zeta$ (Regression coefficients)
- Y (Total expenditure per capita)
- w (Budget share)
- p (Prices)
- ε (Error term)

P is usually given by the Translog price index (Cranfield et al., 2003), but can be linearly approximated by the Stone price index (Deaton and Muellbauer, 1980), which is what we do here as well. This approximation is applied also for QUAIDS (Jones and Mazzi, 1996, Mittal 2010).

The usual restrictions on additivity, symmetry and homogeneity are applied as constraints in the model (see Eqs. (8)–(10)).

Following the approach in Banks et al. (1997) the income and price elasticities are calculated by first differentiating Eq. (1) with respect to $ln\,\overline{Y_c}$ and $ln\,\overline{p_{jc}}$ respectively, where $\overline{Y_c} = \frac{1}{yrs} * \sum_{t=1}^{yrs} Y_{tc}$

$$\overline{p_{jc}} = \frac{1}{yrs} * \sum_{t=1}^{yrs} p_{jct}$$

yrs is the number of years.

$$u_{ic} = \beta_i + \frac{2\gamma_i}{b(p)_c} \lfloor ln\left(\frac{\overline{Y_c}}{\overline{P_c}}\right)\rfloor \quad (2)$$

$$u_{ijc} = \zeta_{ij} - u_i\left(\alpha_{jc} + \sum_{k=1}^{n} \zeta_{jk} \ln p_{kc}\right) - \frac{\gamma_i \beta_i}{b(\boldsymbol{p})_c} \lfloor ln\left(\frac{\overline{Y_c}}{\overline{P_c}}\right)\rfloor^2 \quad (3)$$

Where $b(\boldsymbol{p})_c = \prod_{j=1}^{n} \left[\overline{p_{jc}}^{\beta_j}\right]$ and $\overline{P_c} = \frac{1}{yrs} * \sum_{t=1}^{yrs} P_{tc.}$

The income elasticities are then given by:

$$e_{ic} = \frac{u_{ic}}{\overline{w_{ic}}} \quad (4)$$

Where $\overline{w_{ic}} = \frac{1}{yrs} * \sum_{t=1}^{yrs} w_{itc}$

And the uncompensated price elasticities are given by:

$$e^u_{ijc} = \frac{u_{ijc}}{\overline{w_{ic}}} - \delta_{ij} \quad (5)$$

Where δ_{ij} is the Kronecker delta.

Demand systems typically violate standard assumptions required for OLS being BLUE (best linear unbiased estimator) and, therefore, in these cases, require specific estimation strategies. For this reason we use the single-stage Generalized Maximum Entropy (GME) estimator developed in Golan et al. (2001), which is shown to be robust, consistent and efficient even under non-normal errors and correlated independent variables.

In the QUAIDS model, the estimates of the parameters α_{ic}, ζ_{ij}, β_i and γ_i are found by solving the non-linear program:

$$\begin{aligned}\max S\left(\pi_{\alpha_{ic}}^{m},\pi_{\zeta_{ij}}^{m},\pi_{\beta_i}^{m},\pi_{\gamma_i}^{m},\varphi_{itc}^{n}\right) &= -\sum\nolimits_{ic}^{m}\pi_{\alpha_{ic}}^{m}\ \ln\pi_{\alpha_{ic}}^{m}-\sum\nolimits_{ij}^{m}\pi_{\zeta_{ij}}^{m}\ \ln\pi_{\zeta_{ij}}^{m}\\ &\quad-\sum\nolimits_{i}^{m}\pi_{\beta_i}^{m}\ \ln\pi_{\beta_i}^{m}-\sum\nolimits_{i}^{m}\pi_{\gamma_i}^{m}\ \ln\pi_{\gamma_i}^{m}\\ &\quad-\sum\nolimits_{itc}^{n}\varphi_{itc}^{n}\ \ln\varphi_{itc}^{n}\end{aligned} \tag{6}$$

s.t.

$$\begin{aligned}w_{itc} &= \sum\nolimits_{ic}^{m}\pi_{\alpha_{ic}}^{m}z_{\alpha_{ic}}^{m}+\sum\nolimits_{ij}^{m}\pi_{\zeta_{ij}}^{m}\ z_{\zeta_{ij}}^{m}\ \ln p_{jtc}+\sum\nolimits_{i}^{m}\pi_{\beta_i}^{m}\ z_{\beta_i}^{m}\ \ln\left(\frac{Y_{tc}}{P_{tc}}\right)\\ &\quad+\frac{\sum_i^m \pi_{\gamma_i}^{m}\ z_{\gamma_i}^{m}}{\prod_{j=1}^{n} p_{jtc}^{\left(\sum_i^m \pi_{\beta_i}^{m}\ z_{\beta_i}^{m}\right)}}*\left[\ln\left(\frac{Y_{tc}}{P_{tc}}\right)\right]^2+\sum\nolimits_{itc}^{n}\varphi_{itc}^{n}\sigma_{itc}^{n}\end{aligned} \tag{7}$$

$$\sum_{i=1}^{n}\pi_{\alpha_{ic}}^{m}\ z_{\alpha_{ic}}^{m}=1 \tag{8}$$

$$\sum_{i=1}^{n}\pi_{\beta_i}^{m}\ z_{\beta_i}^{m}=\sum_{i=1}^{n}\pi_{\zeta_{ij}}^{m}\ z_{\zeta_{ij}}^{m}=\sum_{i=1}^{n}\pi_{\gamma_i}^{m}\ z_{\gamma_i}^{m}=0 \tag{9}$$

$$\pi_{\zeta_{ij}}^{m}\ z_{\zeta_{ij}}^{m}=\pi_{\zeta_{ji}}^{m}\ z_{\zeta_{ji}}^{m} \tag{10}$$

$$\sum\nolimits^{m}\pi_{\alpha_{ic}}^{m}=1 \tag{11}$$

$$\sum\nolimits^{m}\pi_{\beta_i}^{m}=1 \tag{12}$$

$$\sum\nolimits^{m}\pi_{\gamma_i}^{m}=1 \tag{13}$$

$$\sum\nolimits^{m}\pi_{\zeta_{ij}}^{m}=1 \tag{14}$$

$$\sum\nolimits^{n}\varphi_{itc}^{n}=1 \tag{15}$$

In the reparametrized version of the QUAIDS Eq. (1), the parameters α_{ic}, ζ_{ij}, β_i and γ_i are replaced by linear combinations of M supports $z_{\alpha ic}^{m}$, $z_{\beta i}^{m}$, $z_{\zeta ij}^{m}$, and $z_{\gamma i}^{m}$, which are discrete points that span uniform intervals, symmetrical around zero that contain all possible values the parameters can take, and weights to be estimated that add up to one, $\pi_{\alpha ic}^{m}$, $\pi_{\zeta ij}^{m}$, $\pi_{\beta i}^{m}$, and $\pi_{\gamma i}^{m}$. Likewise, the error terms ε_{itc} are replaced by a linear combination of the supports σ_{itc}^{n} and weights φ_{itc}^{n}. We follow the approach of Golan et al. (2001) and define $M = 3$ supports for each parameter, namely lower and upper bounds and zero. According to the principle of maximum entropy, maximizing (6) yields the most uniform weights that are consistent with the empirical model subject to the condition that they constitute proper probabilities (i.e. add up to one).

The non-linear program (6) is implemented in GAMS and solved using the non-linear solver CONOPT. The supports for each parameter of the demand system are specified such that their value exceeds the

Table 1
Parameter values for the QUAIDS model. Values marked in green are significant at level v = 0.05 with degrees of freedom = (yrs * nC) − 1: and critical value $t_{crit,\,0.05}$ = 1.963. yrs and nC are the number of years and regions in the input data respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services	β	γ
Vegetables, fruit, nuts, rice and crops	-0.006	0.002	0.001	0.010	0.005	-0.008	-0.003	0.001	-0.004	0.001	0.000	0.003	0.005	0.003	-0.011	-0.036	0.008
Fish, Meat and dairy	0.002	0.007	0.004	-0.003	-0.001	0.011	0.007	-0.002	-0.006	0.003	-0.001	-0.011	0.003	0.001	-0.013	-0.023	0.001
Tobacco and beverages	0.001	0.004	0.006	-0.004	-0.007	-0.017	0.011	-0.007	-0.002	-0.006	0.002	0.009	0.004	-0.015	0.019	-0.002	-0.001
Food nec	0.010	-0.003	-0.004	0.009	0.001	0.010	-0.012	0.001	0.009	0.001	-0.003	0.003	-0.017	0.009	-0.017	-0.017	0.000
Clothing	0.005	-0.001	-0.007	0.001	-0.008	-0.025	0.006	0.008	0.000	0.001	-0.005	0.001	-0.004	0.011	0.015	0.006	-0.003
Housing, real estate, water, gas, electricity and other fuels	-0.008	0.011	-0.017	0.010	-0.025	0.049	-0.012	0.011	-0.001	-0.008	0.015	-0.029	-0.004	-0.001	0.009	-0.003	0.002
Furniture, Household goods and services	-0.003	0.007	0.011	-0.012	0.006	-0.012	0.005	-0.007	-0.004	0.000	0.001	0.002	0.009	-0.011	0.006	0.006	-0.002
Health, education, insurance and social security	0.001	-0.002	-0.007	0.001	0.008	0.011	-0.007	0.013	-0.001	0.004	-0.008	0.001	-0.018	-0.003	0.007	0.005	0.000
Transport services and fuels nec	-0.004	-0.006	-0.002	0.009	0.000	-0.001	-0.004	-0.001	-0.002	0.003	-0.004	0.007	0.001	0.011	-0.008	0.008	0.001
Railway, air and other transportation services	0.001	0.003	-0.006	0.001	0.001	-0.008	0.000	0.004	0.003	0.004	0.003	0.002	-0.008	0.007	-0.006	0.004	-0.001
Communication services	0.000	-0.001	0.002	-0.003	-0.005	0.015	0.001	-0.008	-0.004	0.003	-0.002	0.000	0.008	0.001	-0.007	0.007	0.002
Recreation and culture	0.003	-0.011	0.009	0.003	0.001	-0.029	0.002	0.001	0.007	0.002	0.000	-0.003	-0.003	-0.007	0.023	0.006	-0.001
Restaurants and hotels	0.005	0.003	0.004	-0.017	-0.004	-0.004	0.009	-0.018	0.001	-0.008	0.008	-0.003	0.018	0.001	0.005	0.013	0.001
Motor Vehicles	0.003	0.001	-0.015	0.009	0.011	-0.001	-0.011	-0.003	0.011	0.007	0.001	-0.007	0.001	0.005	-0.012	0.014	-0.003
Miscellaneous goods and services	-0.011	-0.013	0.019	-0.017	0.015	0.009	0.006	0.007	-0.008	-0.006	-0.007	0.023	0.005	-0.012	-0.009	0.012	-0.004

Table 2
Income elasticities for the 49 regions and 15 products. Top and bottom three values per region marked in green and red colors respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services
AT	1.4	0.5	0.4	0.6	0.8	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.1	0.9	0.9
BE	1.2	0.7	0.5	0.8	0.8	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.3	1.0	0.9
BG	0.2	0.8	0.9	0.8	1.1	1.0	1.1	1.2	1.2	1.0	1.1	1.2	1.3	1.7	1.2
CY	0.7	0.7	0.6	0.6	0.8	1.0	0.9	1.1	1.3	1.0	1.3	1.0	1.1	1.0	1.0
CZ	0.5	0.8	0.7	0.8	1.0	1.0	1.0	1.1	1.2	1.1	1.3	1.1	1.2	1.1	1.0
DE	1.4	0.6	0.4	0.7	0.8	1.0	0.9	1.1	1.4	1.0	1.4	1.0	1.3	1.0	0.9
DK	1.5	0.6	0.3	0.7	0.7	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.4	0.9	0.9
EE	0.2	0.8	0.4	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.2	1.3	1.1
ES	1.0	0.7	0.3	0.7	0.8	1.0	0.9	1.1	1.4	1.0	1.5	1.0	1.1	1.0	0.9
FI	1.2	0.7	-0.4	0.7	0.8	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.2	0.9	0.9
FR	1.2	0.7	0.5	0.6	0.8	1.0	0.9	1.1	1.4	1.0	1.4	1.0	1.3	1.0	0.9
GR	1.0	0.7	0.1	0.6	0.8	1.0	0.9	1.1	1.4	1.0	1.6	1.0	1.1	1.0	1.0
HR	0.5	0.8	0.8	0.7	1.0	1.0	1.0	1.2	1.5	1.2	1.3	1.1	1.3	1.1	1.0
HU	0.4	0.8	0.7	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.2	1.1	1.1
IE	1.5	0.6	0.8	0.7	0.8	1.0	0.8	1.1	1.2	1.0	1.4	1.0	1.1	0.9	0.9
IT	1.2	0.7	0.3	0.7	0.9	1.0	0.9	1.1	1.3	1.0	1.5	1.0	1.2	0.9	0.9
LT	0.7	0.8	0.9	0.8	1.0	1.0	1.0	1.2	1.2	1.0	1.3	1.1	1.3	1.1	1.0
LU	1.3	0.3	0.5	0.5	0.7	1.0	0.9	1.1	1.3	1.0	1.6	1.0	1.2	0.9	0.9
LV	0.5	0.8	0.6	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.3	1.2	1.1
MT	0.8	0.8	0.5	0.7	0.9	1.0	1.0	1.1	1.2	1.0	1.2	1.0	1.3	1.0	1.0
NL	1.3	0.6	0.4	0.7	0.8	1.0	0.9	1.1	1.2	1.0	1.3	1.0	1.4	0.9	0.9
PL	0.6	0.8	0.5	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.2	1.1	1.3	1.2	1.0
PT	0.9	0.8	0.6	0.7	0.9	1.0	0.9	1.1	1.4	1.0	1.3	1.0	1.1	1.0	1.0
RO	0.7	0.8	0.9	0.9	1.1	1.0	1.1	1.2	1.3	1.1	1.2	1.3	1.2	1.3	1.1
SE	1.5	0.6	-0.4	0.6	0.6	1.0	0.9	1.1	1.3	1.0	1.4	1.0	1.3	0.9	0.9
SI	0.8	0.8	0.3	0.6	0.9	1.0	1.0	1.1	1.2	1.1	1.3	1.0	1.2	1.0	1.0
SK	0.7	0.7	0.7	0.8	1.0	1.0	1.0	1.1	1.3	1.1	1.3	1.1	1.3	1.2	1.0
GB	1.6	0.6	0.0	0.5	0.7	1.0	0.9	1.1	1.5	1.0	1.5	1.0	1.1	0.9	0.9
US	2.4	0.1	0.6	0.5	0.5	1.0	0.8	1.0	1.6	1.0	1.5	1.0	1.2	0.9	0.9
JP	1.4	0.5	0.8	0.6	0.6	1.0	0.8	1.1	1.4	1.0	1.4	1.0	1.1	0.9	0.9
CN	0.7	0.8	1.0	0.8	1.2	1.0	1.3	1.0	1.4	1.2	1.3	1.5	1.2	1.8	1.1
CA	1.5	0.4	0.7	0.6	0.6	1.0	0.9	1.1	1.4	1.0	1.6	1.0	1.2	0.9	1.0
KR	0.8	0.5	0.7	0.7	0.9	1.0	0.9	1.0	1.4	1.0	1.2	1.0	1.2	1.1	1.0

BR	0.3	0.6	0.8	0.7	1.0	1.0	1.0	1.1	1.2	1.1	2.3	1.1	1.2	1.2	1.0
IN	0.7	0.6	1.0	0.9	1.2	0.9	1.5	1.1	1.2	1.1	1.2	1.9	1.3	2.1	1.2
MX	0.2	0.6	0.9	0.8	1.0	1.0	1.0	1.1	1.3	1.0	1.3	1.1	1.2	1.1	1.0
RU	0.6	0.8	0.9	0.8	1.1	1.0	1.1	1.1	1.3	1.1	1.1	1.2	1.7	1.9	1.1
AU	1.2	0.4	0.7	0.6	0.7	1.0	0.9	1.1	1.5	1.0	1.4	1.0	1.2	1.0	0.9
CH	2.0	-0.7	0.6	0.5	0.5	1.0	0.8	1.0	1.8	1.0	1.5	0.9	1.2	0.8	0.9
TR	0.8	0.1	0.8	0.9	1.0	1.0	1.0	1.2	1.4	1.0	1.3	1.1	1.3	1.3	1.1
TW	0.8	0.6	0.8	0.5	0.8	1.0	0.9	1.0	1.4	1.0	1.2	1.0	1.2	1.0	1.0
NO	1.5	0.6	0.7	0.6	0.7	1.0	0.9	1.1	1.2	1.0	1.4	1.0	1.2	0.9	0.9
ID	0.7	0.8	1.0	0.8	1.3	1.0	1.2	1.2	1.1	1.1	1.2	1.2	1.1	1.3	1.3
ZA	0.1	0.6	0.9	0.8	1.1	1.0	1.1	1.0	1.3	1.0	1.2	1.3	1.3	1.2	1.1
WA	-0.1	0.3	0.9	0.7	1.2	1.0	1.2	1.0	1.2	1.1	1.1	1.2	1.2	1.3	1.1
WL	0.3	0.5	0.8	0.7	1.1	1.0	1.0	1.0	1.4	1.1	1.2	1.1	1.2	1.2	1.1
WE	0.1	0.4	0.9	0.7	1.2	1.0	1.1	1.0	1.3	1.1	1.2	1.1	1.1	1.4	1.1
WF	0.1	0.5	1.0	0.8	1.3	1.0	1.2	1.1	1.2	1.2	1.1	1.2	1.1	1.4	1.2
WM	0.3	0.5	0.9	0.7	1.1	1.0	1.1	1.1	1.3	1.1	1.2	1.1	1.2	1.2	1.1

estimates of the corresponding parameter typically found in empirical applications by several orders of magnitude.

The ζ, β, and γ parameters from Eq. (1) are presented in Table 1 (All elasticities and regression coefficients are available in S10).

The *t*-tests on regression coefficients in the full QUAIDS model show that 216 out of 225 (96%) of the ζ_{ij}, all 15 of the β_i, and 14 out of 15 (93%) of the γ_i are significantly different from zero.

The estimated income elasticities are displayed in Table 2.)

The elasticities show clear trends of which products are necessities and luxuries, indicated by the number of red and green values per column. "Communication services", "Transport services and fuels nec", and "restaurants and hotels" are luxury goods, while "food nec", "fish, meat, and dairy" and "tobacco and beverages" are necessities. Interestingly, "vegetables, fruit, nuts, rice, and crops" and "clothing" show a clear distinction of being necessities in developing regions and luxuries in developed regions.

All own-price elasticities are negative (Table 3) and hence the concavity of the underlying expenditure function is fulfilled.

"Vegetables, fruit, nuts, rice, and crops", "clothing" and "miscellaneous goods and services" stand out as product groups that are sensitive to increasing prices, while consumption of "tobacco and beverages" and "restaurants and hotels" are affected less by a price increase. Regional differences are apparent for "housing, real estate, water, gas, electricity and other fuels", where consumption is less affected by a price increase in developing regions than developed ones.

2.3. Statistical tests

We assess the QUAIDS model's goodness of fit by estimating the information inaccuracy (IIA) for the demand system and root mean squared error (RMSE) measures by region, product and for the whole demand system equivalent to the approach in Cranfield et al. (2003). Furthermore, as shown in Golan et al. (2001), the GME estimator is consistent and asymptotically normal. Hence, we perform t-tests on the regression coefficients to test whether they are significantly different from zero. For the goodness of fit measures and t-tests we compare the QUAIDS model with nested models that include different variations of the regression coefficients in Eq. (1). We also compute the log-likelihood ratio statistic to test the significance of the quadratic income term in Eq. (1). For a full overview of the model comparisons, and the calculations of the statistical measures, see S9.

As a justification for using the QUAIDS versus the AIDS specification, we tested the significance of the quadratic income term by checking the log-likelihood ratio statistic (S9 eq. S17) against the critical value in the χ^2-distribution. We find that the quadratic term is significant at level $v = 0.01$ (see S9 for calculation steps and test values). The IIA and system-wide RMSE results show that the full QUIADS model performs best, which corresponds well with the equivalent findings in Cranfield et al. (2003). For the product-wise RMSE, the full QUAIDS model performs best (9 of 15 cases), while the model where the price terms (ζ_{ij}) are restricted to zero and the model with the quadratic income term (γ_i) restricted to zero perform second best of all the models (best in 2 out of 15 cases each). For regional RMSE, the full QUAIDS model again performs best (15 out of 49 cases). Second are the model with the quadratic income term (γ_i) removed and the model with all terms except the intercept (α_{ic}) restricted to zero (best in 6 out of 49 cases each). From this we conclude that allowing for non-linear Engel curves overall improves the model performance, with a few exceptions in some regions. The good performance for some products using the specification without price terms (price terms set to zero) can be related to the uncertainty in the price information used in EXIOBASE 3, which is gathered from several different data sources (Stadler et al., 2018).

2.4. Forecasting total household demand/expenditure

Based on the regression results, scenarios of changes in consumption are constructed consistent with exogenous scenarios of population growth and affluence growth. Projections of population are based on the Medium Variant projection from the 2015 Revision of population projections made by the United Nations (UN, 2015). The population projections for 230 countries are available, and were aggregated according to the EXIOBASE region definition, from which population growth rates are calculated.

Table 3
Own-price elasticities for the 49 regions and 15 products. Top and bottom three values per region marked in green and red colors respectively.

	Vegetables, fruit, nuts, rice and crops	Fish, Meat and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity and other fuels	Furniture, Household goods and services	Health, education, insurance and social security	Transport services and fuels nec	Railway, air and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor Vehicles	Miscellaneous goods and services
AT	-1.27	-0.78	-0.61	-0.77	-1.20	-0.82	-0.90	-0.82	-1.04	-0.92	-1.06	-1.06	-0.88	-0.91	-1.11
BE	-1.22	-0.84	-0.62	-0.85	-1.19	-0.83	-0.87	-0.86	-1.04	-0.76	-1.06	-1.07	-0.71	-0.93	-1.09
BG	-1.15	-0.91	-0.85	-0.89	-1.20	-0.83	-0.86	-0.63	-1.05	-0.95	-1.04	-1.09	-0.62	-0.68	-1.19
CY	-1.40	-0.86	-0.68	-0.79	-1.28	-0.79	-0.86	-0.84	-1.05	-0.95	-1.05	-1.09	-0.90	-0.90	-1.13
CZ	-1.17	-0.89	-0.67	-0.87	-1.18	-0.84	-0.90	-0.67	-1.04	-0.87	-1.06	-1.07	-0.75	-0.89	-1.11
DE	-1.33	-0.82	-0.58	-0.80	-1.21	-0.84	-0.89	-0.85	-1.05	-0.90	-1.06	-1.06	-0.74	-0.94	-1.08
DK	-1.24	-0.82	-0.52	-0.83	-1.24	-0.86	-0.88	-0.84	-1.04	-0.84	-1.06	-1.05	-0.63	-0.88	-1.06
EE	-1.22	-0.92	-0.33	-0.88	-1.16	-0.83	-0.89	-0.68	-1.05	-0.92	-1.05	-1.06	-0.76	-0.78	-1.13
ES	-1.18	-0.84	-0.44	-0.84	-1.26	-0.79	-0.85	-0.78	-1.05	-0.87	-1.07	-1.05	-0.93	-0.92	-1.12
FI	-1.25	-0.86	-0.02	-0.83	-1.26	-0.86	-0.87	-0.79	-1.04	-0.90	-1.06	-1.05	-0.77	-0.88	-1.10
FR	-1.21	-0.87	-0.66	-0.77	-1.25	-0.85	-0.88	-0.82	-1.05	-0.91	-1.06	-1.06	-0.75	-0.94	-1.09
GR	-1.13	-0.87	-0.35	-0.78	-1.19	-0.81	-0.79	-0.85	-1.06	-0.93	-1.09	-1.06	-0.90	-0.82	-1.08
HR	-1.13	-0.91	-0.75	-0.80	-1.15	-0.84	-0.94	-0.63	-1.09	-0.75	-1.07	-1.05	-0.69	-0.90	-1.10
HU	-1.16	-0.90	-0.67	-0.87	-1.21	-0.80	-0.89	-0.78	-1.06	-0.90	-1.05	-1.06	-0.76	-0.92	-1.11
IE	-1.41	-0.83	-0.83	-0.82	-1.24	-0.81	-0.82	-0.83	-1.04	-0.93	-1.05	-1.05	-0.87	-0.83	-1.09
IT	-1.14	-0.86	-0.53	-0.79	-1.10	-0.81	-0.92	-0.74	-1.05	-0.88	-1.07	-1.07	-0.85	-0.92	-1.10
LT	-1.07	-0.91	-0.85	-0.86	-1.18	-0.79	-0.91	-0.66	-1.05	-0.93	-1.06	-1.09	-0.69	-0.88	-1.12
LU	-1.11	-0.67	-0.70	-0.68	-1.24	-0.86	-0.88	-0.78	-1.04	-0.87	-1.07	-1.08	-0.81	-0.93	-1.07
LV	-1.11	-0.90	-0.52	-0.89	-1.19	-0.82	-0.88	-0.75	-1.05	-0.92	-1.05	-1.05	-0.67	-0.89	-1.16
MT	-1.17	-0.89	-0.59	-0.83	-1.14	-0.76	-0.93	-0.75	-1.04	-0.94	-1.04	-1.06	-0.66	-0.91	-1.10
NL	-1.23	-0.79	-0.57	-0.84	-1.21	-0.83	-0.87	-0.89	-1.04	-0.88	-1.05	-1.06	-0.66	-0.90	-1.08
PL	-1.12	-0.91	-0.42	-0.88	-1.23	-0.83	-0.89	-0.72	-1.05	-0.90	-1.05	-1.10	-0.62	-0.87	-1.09
PT	-1.18	-0.88	-0.64	-0.82	-1.11	-0.75	-0.90	-0.85	-1.06	-0.86	-1.05	-1.08	-0.87	-0.94	-1.11
RO	-1.06	-0.92	-0.78	-0.91	-1.21	-0.81	-0.88	-0.61	-1.06	-0.93	-1.06	-1.21	-0.76	-0.87	-1.20
SE	-1.33	-0.83	-0.07	-0.78	-1.35	-0.86	-0.86	-0.83	-1.05	-0.90	-1.05	-1.04	-0.69	-0.89	-1.07
SI	-1.16	-0.89	-0.42	-0.77	-1.18	-0.82	-0.91	-0.82	-1.04	-0.84	-1.06	-1.05	-0.80	-0.93	-1.14
SK	-1.09	-0.88	-0.64	-0.86	-1.14	-0.83	-0.91	-0.70	-1.05	-0.91	-1.06	-1.07	-0.65	-0.87	-1.10
GB	-1.34	-0.79	-0.33	-0.73	-1.25	-0.83	-0.88	-0.82	-1.07	-0.93	-1.06	-1.05	-0.90	-0.92	-1.10
US	-1.49	-0.56	-0.73	-0.68	-1.35	-0.80	-0.83	-0.95	-1.07	-0.81	-1.06	-1.04	-0.79	-0.89	-1.06
JP	-1.21	-0.74	-0.83	-0.77	-1.32	-0.82	-0.83	-0.86	-1.05	-0.92	-1.05	-1.05	-0.88	-0.89	-1.10
CN	-1.00	-0.91	-0.49	-0.86	-1.16	-0.68	-0.86	-0.88	-1.11	-0.86	-1.13	-1.18	-0.77	-0.83	-1.09
CA	-1.35	-0.74	-0.82	-0.75	-1.34	-0.83	-0.88	-0.88	-1.06	-0.83	-1.07	-1.04	-0.78	-0.92	-1.06
KR	-1.13	-0.80	-0.74	-0.80	-1.22	-0.74	-0.76	-0.93	-1.06	-0.93	-1.04	-1.05	-0.84	-0.81	-1.10

BR	-1.18	-0.85	-0.75	-0.80	-1.16	-0.64	-0.83	-0.88	-1.04	-0.91	-1.24	-1.06	-0.73	-0.88	-1.04
IN	-0.99	-0.86	-0.78	-0.92	-1.14	-0.65	-0.79	-0.85	-1.08	-0.94	-1.17	-1.30	-0.54	-0.82	-1.13
MX	-1.26	-0.85	-0.84	-0.90	-1.31	-0.77	-0.85	-0.75	-1.06	-0.97	-1.06	-1.09	-0.77	-0.93	-1.08
RU	-1.05	-0.91	-0.91	-0.90	-1.19	-0.72	-0.84	-0.74	-1.07	-0.93	-1.04	-1.10	-0.08	-0.63	-1.07
AU	-1.20	-0.74	-0.82	-0.74	-1.26	-0.82	-0.87	-0.88	-1.07	-0.95	-1.06	-1.04	-0.78	-0.92	-1.08
CH	-1.25	-0.22	-0.77	-0.71	-1.31	-0.84	-0.85	-0.94	-1.08	-0.90	-1.06	-1.14	-0.82	-0.83	-1.06
TR	-1.05	-0.66	-0.75	-0.91	-1.09	-0.78	-0.89	-0.52	-1.07	-0.97	-1.06	-1.12	-0.70	-0.81	-1.12
TW	-1.15	-0.83	-0.78	-0.69	-1.43	-0.80	-0.87	-0.90	-1.06	-0.93	-1.05	-1.06	-0.81	-0.91	-1.08
NO	-1.22	-0.81	-0.77	-0.78	-1.27	-0.83	-0.89	-0.77	-1.03	-0.93	-1.05	-1.05	-0.82	-0.91	-1.10
ID	-1.01	-0.91	-0.88	-0.84	-1.31	-0.57	-0.88	-0.62	-1.04	-0.94	-1.07	-1.09	-0.89	-0.94	-1.18
ZA	-1.17	-0.84	-0.89	-0.88	-1.17	-0.77	-0.88	-0.92	-1.06	-0.95	-1.06	-1.17	-0.66	-0.92	-1.18
WA	-1.15	-0.78	-0.72	-0.83	-1.17	-0.74	-0.88	-0.89	-1.06	-0.89	-1.03	-1.07	-0.79	-0.92	-1.08
WL	-1.14	-0.83	-0.76	-0.82	-1.23	-0.76	-0.90	-0.91	-1.07	-0.88	-1.05	-1.05	-0.80	-0.92	-1.08
WE	-1.12	-0.80	-0.77	-0.84	-1.25	-0.79	-0.89	-0.89	-1.07	-0.88	-1.06	-1.07	-0.83	-0.89	-1.08
WF	-1.09	-0.85	-0.81	-0.85	-1.22	-0.74	-0.90	-0.87	-1.07	-0.89	-1.05	-1.07	-0.83	-0.93	-1.09
WM	-1.13	-0.82	-0.76	-0.82	-1.21	-0.79	-0.88	-0.88	-1.05	-0.90	-1.06	-1.06	-0.80	-0.92	-1.08

We model growth in affluence using the projections of economic indicators from the International Energy Agency's Energy Technology Perspectives, IEA ETP (IEA, 2015).[2] It provides long-term compound growth rate projections of GDP for the World, OECD countries, Non-OECD countries, ASEAN, Brazil, China, European Union, India, Mexico, Russia, South Africa and the United States (see S6). For the years up to 2022, the IMF medium term forecast has been used for the all regions in EXIOBASE. For the years after, the relative distance between the region's growth rate in 2022 and the average annual growth rate of the corresponding region in the IEA ETP data for the years 2020–2030 has been used.

GDP is a measure of the output of a country but does not fully represents that country's consumption as it includes exports and excludes imports. Therefore, we estimate household consumption development relative to GDP using simple ordinary least squares regressions (S5). In a last step, we apply the obtained growth rates in future consumption to the consumption data of 2011 from EXIOBASE 3 to ensure consistency with historic data when projecting into the future.

2.5. Calculating scenarios of GHG emissions based on forecasted demand

Impacts (I) of changing population (P), affluence (A) and technological change (T) on the environment are often modelled using the IPAT concept (Ehrlich and Holdren, 1971). Here we focus only on the effect of changes in affluence on consumption and through this, the impact on the environment. In the static scenario, we assume no changes in household preferences by projecting the 2011 EXIOBASE expenditure shares. In the QUAIDS scenario we estimate the QUAIDS model (Eq. (1)) to calculate the projected expenditure shares. Note that all scenarios are based on the same forecasted population and expenditure. To isolate the effect of changing consumption structure on environmental impacts, we use 2011 Leontief multipliers (which show impact per unit of final consumption) for all projections. These product-specific multipliers are calculated to include direct household emissions (by product) as well as the indirect emissions via the Leontief inverse as is common in the calculation of carbon footprints (Ivanova et al., 2016). Therefore, our scenarios are purely based on the sensitivity of different ways to attribute increasing consumption to categories of products: no technological change, price responses, divestment from fossil fuels or energy efficiency improvements are considered.

For calculating total environmental impacts of household consumption, we firstly estimate the 2011 multiplier for each country c of the model individually to include both indirect emissions and direct household emissions (see below for nomenclature):

$$\mathbf{q_c}^{2011} = \left[\left(\mathbf{b}*((\mathbf{S}*\mathbf{L})+\mathbf{S_{hh}})*\widehat{\mathbf{y}^{mr}_{hh,c}}\right)*\mathbf{G}\right]*\left(\widehat{\mathbf{y}^{mr}_{hh,c}*\mathbf{G}}\right)^{-1} \tag{16}$$

Whilst the equation looks complex compared to a conventional multiplier calculation, it is simply keeping the detail on products consumed by households for the region of consumption, and creates weighted average multipliers of goods consumed by that region – that is, it aggregates the multi-regional dimension of the multipliers. Hence Eq. (16) shows a diagonalization of the footprint calculation in order to maintain the product disaggregation, followed by an aggregation of the footprint, before division by the expenditure on each product group (also aggregated to remove the regional dimension). Eq. (16) also includes intensities for household emissions (such as household use of a vehicle) which are obtained by dividing the fuel use emissions of a certain good by the expenditure on that good.

We then estimate the carbon footprint[3] for different countries c and years t using the projections of per-capita expenditure Y_{tc} from the GDP regressions (Section 2.4) and estimated household budget shares $\mathbf{w_{tc}}$ from the demand model (Section 2.2) as:

$$\mathbf{e_{tc}} = \left(\mathbf{q_c}^{2011}*\widehat{\mathbf{w_{tc}}}*Y_{tc}\right)*pop_{tc} \tag{17}$$

[2] https://www.iea.org/etp/etpmodel/assumptions/

[3] The carbon footprint (CF) is the weighted sum of GHG emissions according to their global warming potential. From the result section and onwards, results are shown as carbon footprints, not the individual GHGs. The terms CF and GHG are both used but refer to the same unit of measurement.

Letting nG, nC and nS represent the number of GHGs, regions, and sectors respectively, in EXIOBASE, whilst nAggS represents the 15 product groups used in the demand model, the nomenclature is:

$\mathbf{e_{tc}}$ vector of total environmental carbon footprint by product for each country c and year t [1 x nAggS]

$\mathbf{b}$ vector of characterization factors linking the global warming potential of different GHGs to carbon footprint in CO_2-equivalents [1 x nG]

$\mathbf{S}$ matrix of GHG emission per unit of production [nG x nC*nS]

$\mathbf{L}$ Leontief inverse matrix [nC*nS x nC*nS]

$\mathbf{shh}$ vector of GHG emission per unit of household expenditure directly emitted by households. [nG x nC*nS]

$\mathbf{G}$ Binary aggregation matrix to aggregate both the region of production of goods as well as from the EXIOBASE classification to the 15 sectors used in the demand model [nC*nS x nAggS]

$\mathbf{y}_{hh,c}^{mr}$ vector of household consumption from EXIOBASE (showing goods produced in any region, but consumed in country c) [nC*nS x 1]

$\mathbf{q}_c^{2011}$ vector of GHG multipliers (emissions per unit of final expenditure) based on the Leontief production function for 2011 in country c, aggregated to nAggS products consumed in the country. [1 x nAggS]

pop_{tc} the population projection for year t and region c $[1 \times 1]$

The "hat" means diagonalization of a vector.

This derivation implies that elements in Eq. (17) change according to the population and affluence projections, as well as the difference in w_{tc} between the scenarios we investigate (QUAIDS and static), while $\mathbf{q}_c^{2011}$ remains unchanged. Furthermore, the traded expenditure of $\mathbf{y}_{hh,c}^{mr}$ and the shares of sub-products contained in the same product group in the QUAIDS model remain equal to the 2011 values in the projections. Further analysis on these points is in the discussion. More details about MRIO methods and calculations can be found in S7.

In the future scenarios the new total expenditure per region obtained from the exogeneous projections is applied to Eq. (1) with prices assumed to be constant (i.e. equal to 2011 prices = 1 for future years). Then the carbon footprints are calculated in Eq. (17) The modelling steps described in the sections above are illustrated in Fig. 1.

3. Results

The income elasticities for the 15 products in Table 2 are presented in Fig. 2 according to the expenditure per capita of each of the 49 regions (bubble size) and the global average elasticity weighted by each region's share of global expenditure in 2011 (black horizontal lines).

The difference between developing and developed regions for certain product groups discussed under Table 2 become evident for additional product groups such as "motor vehicles" and "furniture and household goods". The degree of variance between regional elasticities highly varies. "Vegetables, fruit, nuts, rice and crops" has the highest variation between 0.1 (RoW Asia) and 2.4 (USA). The preference for "health, education, insurance, and social security" is quite uniform between 1.0 (USA) and 1.2 (Turkey). "Housing, real estate, water, gas, electricity and other fuels" is even less elastic with values between 0.9 (India) and 1.0 (USA). The highest global weighted average elasticity is found for "transport services and fuels nec" (1.4) and is the results of large elasticities for regions contributing to a large share of the global total expenditure such as the US (1.6), Great Britain (1.5) and China (1.4). "Fish, meat, and dairy" has the lowest global weighted average elasticity value (0.6) with countries such as Switzerland (−0.7) and USA (0.1) contributing to the low value.

When ranking the top and bottom three regional elasticities per product group, some regions show consistently more extreme elasticities than others. The US has bottom three elasticities for seven of the product groups, and top three elasticities for two product groups. India has five product groups that rank in the top three and one in the bottom three. China has one bottom three elasticity and four top three ones. Switzerland has two top three elasticities and six bottom three ones. RoW Africa has three top three elasticities and one ranking in the bottom three.

Future population, expenditure per capita, and the GHG intensity of consumption for six aggregate regions (See S1 for regional aggregation) are displayed in Fig. 3.

Population is expected to increase by over 30% for the RoW region, with more moderate growth in the other regions, and even decline in Rest of EU by 2030 (Fig. 3A). The BRICS (Brazil, Russia, India, China and South Africa) and RoW have the highest expected growth in expenditure per capita. The already affluent regions EU15 + NO, North America, and other OECD have lower expected expenditure growth at 10–15% over 2011 values (Fig. 3B). The GHG intensity of consumption (Fig. 3C) increases the most for Other OECD and BRICS, while it remains constant or slightly decreases for RoW and EU15 + NO.

Fig. 4 shows the forecasted GHG emissions per capita (Fig. 4A) for the static scenario (dashed lines) and the QUAIDS scenarios (solid lines), and cumulative total emissions (Fig. 4B) for six aggregate regions for the QUAIDS scenario compared to the static scenario.

The largest relative difference in emissions between the scenarios are in the RoW and the BRICS regions, where the QUAIDS scenario results in lower emissions than the static scenario. These two regions also have the lowest emissions per capita. The QUAIDS scenario results in a cumulative 1% lower GHG emissions compared to the static scenario by 2030 globally (Fig. 4B). The differences in cumulative emissions in the populous BRICS and RoW are 1.5–2% lower in the QUAIDS scenario, which largely explains the cumulative lower global emissions in the QUAIDS scenario. The causes of these declining trend in emissions are further explored in Fig. 5 and Fig. 6.

Fig. 5 shows the relative difference in GHG emissions of the QUAIDS scenario compared to the static scenario per product group.

Globally (global expenditure and GHG emissions in S3) there is relatively higher demand and resulting GHG emissions[4] of particularly "Railway-, air-, and other transportation services" in the QUAIDS scenario. Demand and emissions for "vegetables, fruit, nuts, rice and crops" and "fish, meat and dairy" is however about 20% lower than in the static scenario. The direction of the graphs directly follows the trends observed in Fig. 2, and thus the GHG emissions (and expenditure shown in S4) are increasing for "communication services" and "transport services and fuels nec" that have income elasticities above unity in all regions. Compared to the static scenario, "transport services and fuels nec" is the product group with the largest increase in RoW Other OECD, and Rest of EU, while "communication services" increase the most in BRICS in the QUAIDS scenario. Similarly, income elasticities lower than unity in almost all of the 49 regions lead to decreasing GHG emissions in all aggregate regions for "tobacco and beverages" and "fish, meat, and dairy". In the QUAIDS scenario compared to the static scenario. The highly varying trends in income elasticities for "vegetables, fruit, nuts, rice, and crops" observed in Fig. 2 results in highly differing trends in future GHG emissions between regions in the QUAIDS scenario. While the GHG emissions are lower in RoW, BRICS, and Rest of EU, it is the product group that sees GHG emissions increase the most in North America and EU15 + NO in the QUAIDS scenario relative to the static scenario. Globally however, "vegetables, fruit, nuts, rice, and crops" is the product group with the largest decrease in both expenditure and emissions in QUAIDS compared with the static scenario, suggesting that the large populations in particularly BRICS and RoW more than cancels out the increasing trends observed for EU15 + NO and North America. The contribution of different product groups is further explored in Fig. 6 which shows

[4] Note that on a global and aggregated regional level, the observed difference between the expenditure graph (S3) and the GHG emission graph (Figure 5) for a particular product group is purely due to the fact that the sum of all household expenditure in a particular region differs between regions. For a single region, a 1% increase in expenditure on a specific product group will always correspond to a 1% increase in GHG emissions for that product group.

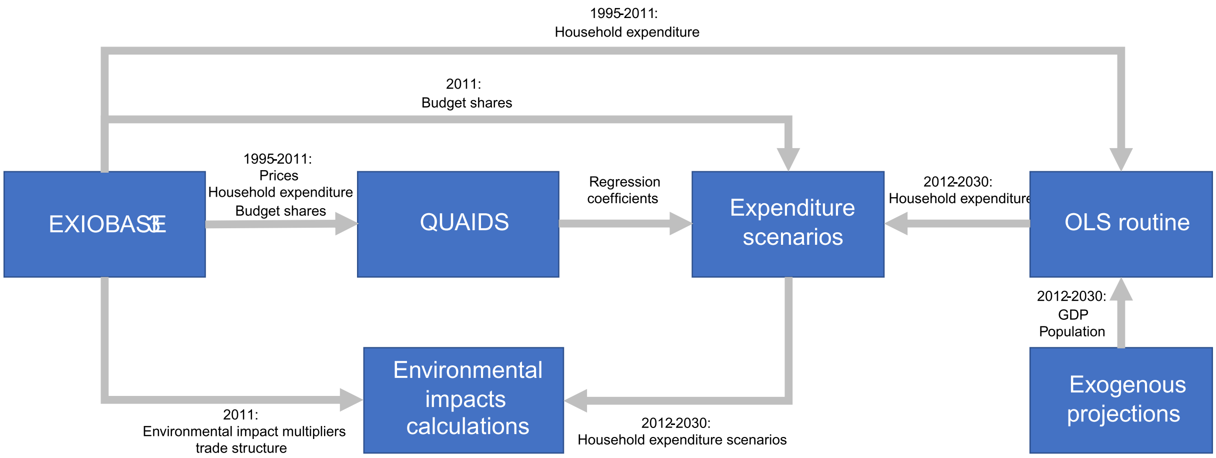

Fig. 1. Overview of the model.

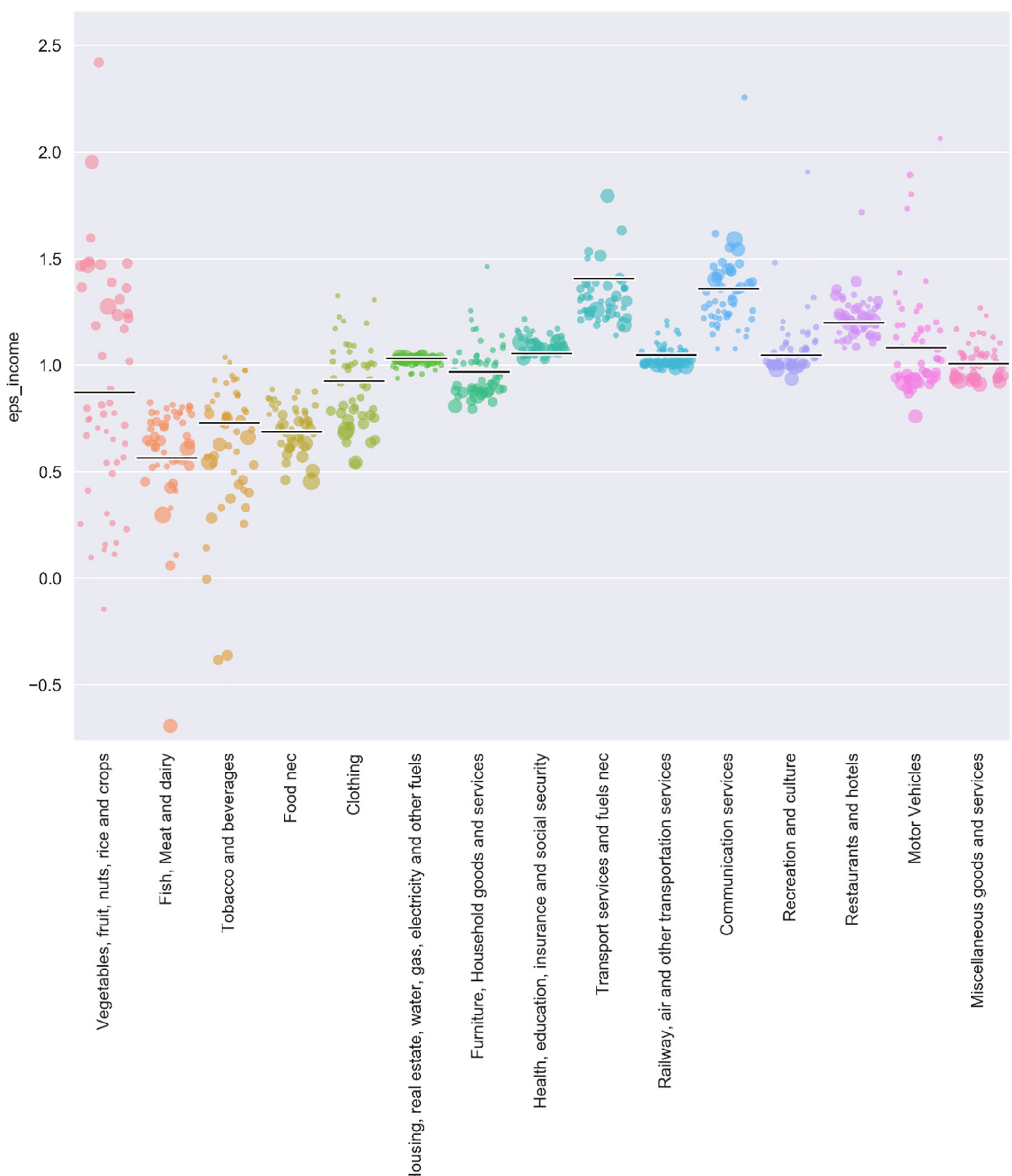

Fig. 2. Value of income elasticities (vertical axis) for the 15 product groups (horizontal axis) and the 49 regions with bubble sizes representing the 2011 expenditure/cap value of each region. The global average elasticity weighted by regional share of global expenditure in 2011 is indicated by black horizontal lines for each product group.

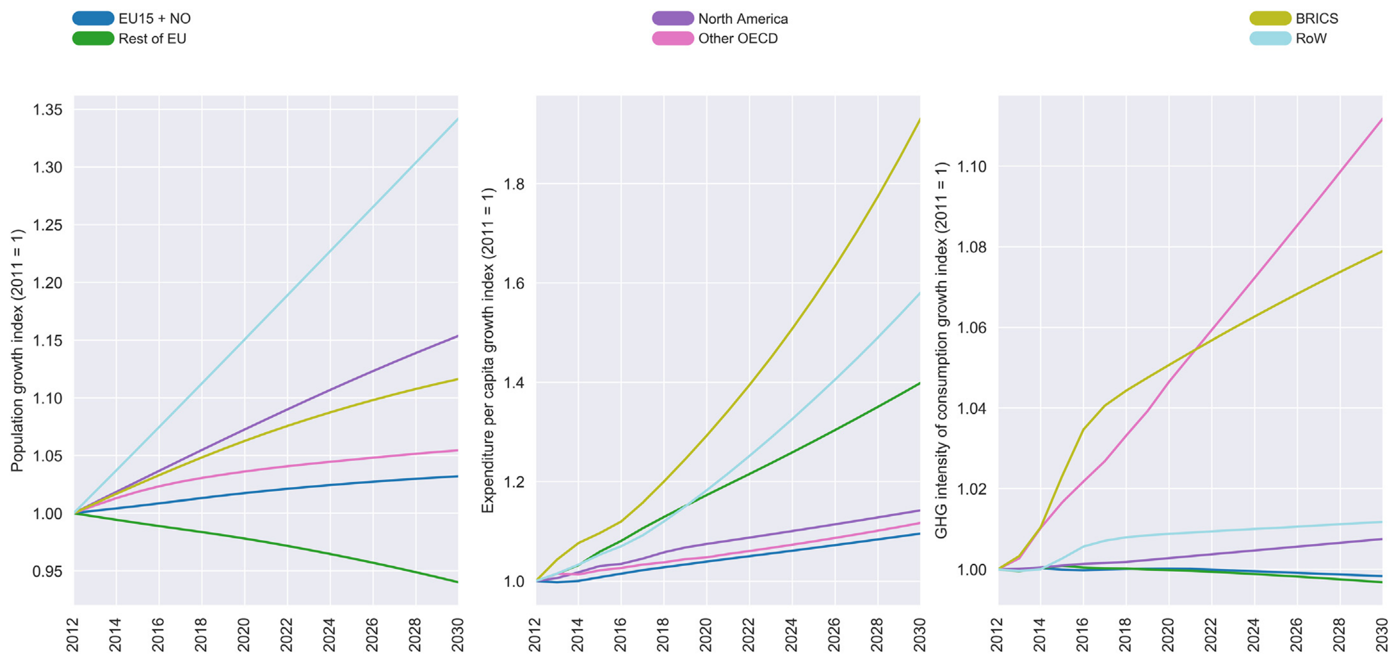

Fig. 3. Evolution of future (A - left) population, (B - middle) expenditure/cap and (C - right) GHG intensity of consumption for the QUAIDS scenario.

the relative contribution of product groups to total emissions in 2030 for the six regions and the 15 product groups used as input to the demand system.

Although the relative difference in GHG emissions between the scenarios is large for e.g. "Transport services and fuels nec" in the BRICS and RoW regions, the contribution to total GHG emissions is quite small. On the other hand, in both RoW and BRICS the decrease in emissions from "vegetables, fruit, nuts, rice, and crops" and "fish, meat, and dairy" is substantial in the QUAIDS scenario relative to the static scenario. This decrease is significant in explaining the declining trend in emissions observed for these regions in Fig. 4B. For North America and EU15, the relative increase in emissions in QUAIDS compared to the static scenario for "vegetables, fruit, nuts, rice, and crops" has small absolute effects on total emissions due to small budget shares in 2011. Overall, the lower emissions from the food product groups in these two regions are cancelled out by higher emissions in the transportation product groups. For all regions, "housing, real estate, water, gas electricity and other fuels" is the largest contributor to emissions. This product group is the most inelastic to changes in expenditure levels (see Fig. 2), observed through small changes in absolute emissions between the scenarios for all regions.

Country and product comparisons for employment, water consumption, material extraction, energy use and land use are available in S2. We find that the QUAIDS scenario results in lower impacts in all regions in four out of these five categories. Only energy use is higher in the static scenario. The largest deviations between the two scenarios are again found for the RoW and BRICS regions, and all regions show the same trend within each product group (i.e. lower impacts for all regions in four out of the five impact categories except for energy use).

We suggest policy recommendations in the form of focal areas of household consumption with the aim of lowering household carbon footprint (CF) based on the outcome of the projections in the QUAIDS scenario Table 4. We investigate the CF share and the CF intensity per monetary unit in 2012 compared to the CF share and intensity of an average product group in the same year. In addition, we look at the changes in household demand in 2030 relative to that in 2012. Hence, a high increase in demand by 2030 combined with a high GHG intensity and share is an indication of important focal areas for lowering consumption-based emissions.

The expected increase in affluence for the developing RoW and BRICS regions are clearly seen with sharp increases in demand per capita from 2012 to 2030 for most product groups (for equivalent country-specific results, see S8). Policies for reducing household emissions in these regions should focus on the "housing, real estate, water, gas, electricity, and other fuels" product group, but also "transport services and fuels nec" and "food nec" due to high GHG intensity and sharp increases in future demand. In North America, demand per capita is expected to increase for all product groups, but the development is most critical regarding emissions from "transport services and fuels nec" with sharp increases in demand, high GHG intensity and high GHG shares. The second product group to focus on in North America is "housing, real estate, water, gas, electricity and other fuels", but this product group has a somewhat lower GHG intensity. These two product groups are essential also in EU15 + NO. Although the expected demand increase is not as high as in North America, the high CF share and intensity indicates that they are key to reducing household impacts. For EU15 + NO and Other OECD there is an expected decrease in demand per capita for some of the product groups, particularly for the food product groups as the previous results (Fig. 5 and Fig. 6) also indicate.

4. Discussion

4.1. Policy implications

Understanding and projecting possible futures is one of the most important tasks in sustainability science and policies as stated in the IPCC Fifth Assessment Report (Edenhofer et al. 2014) and the Shared Socio economic Pathways (Riahi et al., 2017). Given the rise in global wealth, and the strong correlation between wealth and emissions, it is fundamental to understand the potential changes in consumption and its effects on global emissions. Households contribute to the majority (60%) of global GHG emissions (Ivanova et al., 2016), which underlines the importance of understanding how households in countries in different stages of development change their consumption habits as their income changes. We complement the existing forecasting tools by only focusing on the impact of future household preferences on GHG emissions using historic expenditure data from EXIOBASE 3.

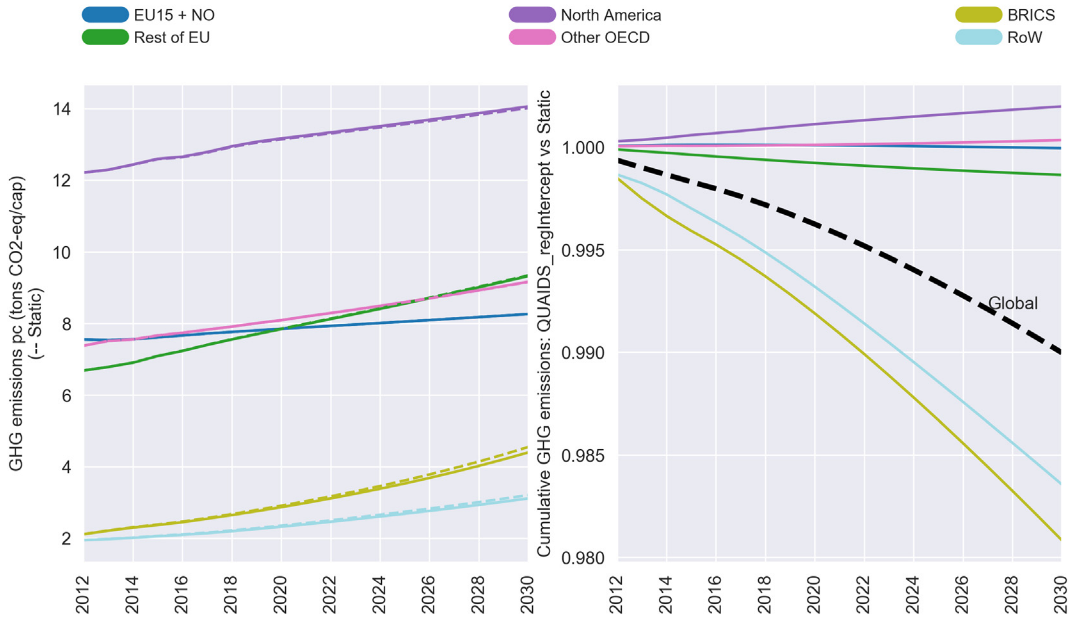

Fig. 4. A (left): Future GHG emissions per capita for the static scenario (dashed lines) and the QUAIDS scenario (solid lines). B (right): Relative deviation from the static scenario (equal to one) for cumulative GHG emissions from 2011 per region for the QUAIDS scenario. Global emissions in dashed lines.

On a global level (see S3), we find a clear tendency towards lower demand and associated impacts for the food product groups in the QUAIDS scenario. Lower-than-unity elasticities for food has strong support in the literature (see e.g. Seale Jr. et al. (2003), Almon (1998), (Muhammad et al., 2011)). Like Almon (1998), we find strong income effects on expenditure for transport, communication, and restaurants and hotels (Fig. 2). The "housing, real estate, water, gas, electricity and other fuels" and "transport services and fuels nec" product groups alone make up about 50% of the global household carbon footprint in 2012 (S3), but add up to less than 30% of household expenditure in 2012, which indicates a high emission multiplier per monetary unit as verified in S3. This contrasts with "health, education, insurance, and social security", which makes up 13% of expenditure in 2012, but only 4% of emissions. The "transport services and fuels nec" product group globally have high income elasticities, while "housing, real estate, water, gas, electricity, and other fuels" behaves like a normal good with an income elasticity around one (see Fig. 2, Fig. 5 and S3), which also has support in the literature (Muhammad et al., 2011). The emission intensities of the three food product groups are all among the highest five out of the 15 product groups globally in 2012 (S3). The combination of low income elasticities and significant share of total household GHG emissions (21%) makes these the main drivers for lower global GHG emissions in the QUAIDS scenario compared to the static scenario. The product group that contributes most to lower relative emissions in the QUAIDS scenario is "vegetables, fruit, nuts, rice and crops".

Our results indicate that accounting for household preferences for products in emission forecasting can have a negative impact on cumulative GHG emissions of up to 2% by 2030 for some of the aggregate regions (Fig. 4) and up to 4% for the individual regions of EXIOBASE (S8). Considering these results, we argue that regional-specific policies aimed towards household consumption can be an important contribution in mitigating global warming. In Table 4 and S8 we provide a guide for policy makers on areas of prioritizing based on our results for the six aggregate regions and each of the 49 regions respectively. The cumulative emissions by 2030 (Fig. 4) shows that the difference in total emissions for developed regions is minimal between the scenarios, while the largest relative decrease in emissions is found in developing regions. From S8 we see that the largest relative cumulative decreases compared to the static scenario are found in India (95.8%), RoW Asia (97.0%) and RoW Africa (98.1%).

Given the rapid changing technology of the last decades, we expect a decrease in the GHG emission intensity of most consumption categories. These technology improvements will have differing effects on the GHG intensity of consumption for different product groups. The electricity sector is in general considered a sector that is relatively easy to decarbonize compared to other sectors, and one which is expected to play a vital role in climate change mitigation (de Sisternes et al., 2016). The transport sector is expected to be more difficult to decarbonize (Kriegler et al., 2014). The same holds for the food sector, which is less dependent on energy and therefore expected to benefit less from the energy transition. Such "hard-to-abate" sectors depend on efficiency improvements or demand side changes to achieve emission reductions. Our results indicate that the relative contribution of food consumption to total emissions is less prominent in the future, which indicates some decarbonization on the demand side. In contrast, the transport sector is expected to have a more significant contribution to total emissions in most countries when considering household preferences (S8). As efficiency improvements, particularly in the energy sector, are susceptible to rebound effects (Sakai et al., 2018, Sorrell, 2014), demand side changes are likely to play a much more prominent role in climate change mitigation in the future.

Our results shed light on the untapped potential of environmental taxation (OECD 2015). Countries that enforce higher environmental taxation as share of GDP, such as Denmark and the Netherlands (OECD 2019) are indeed among the countries in which we have seen the largest decrease in carbon footprint per capita throughout the time series of EXIOBASE (S8). Our results on consumer preferences combined with environmental intensities provide a suitable tool for predicting the effectiveness of environmental taxation which will have different distributional impacts when applied to different goods. Taxes applied for example to domestic heating and electricity are typically found to be regressive, while transport-related taxes are found to be less regressive or even progressive (Milne and Andersen, 2012). Knowledge about this could direct taxation towards largest emission reductions without burdening low-income households (Milne and Andersen, 2012).

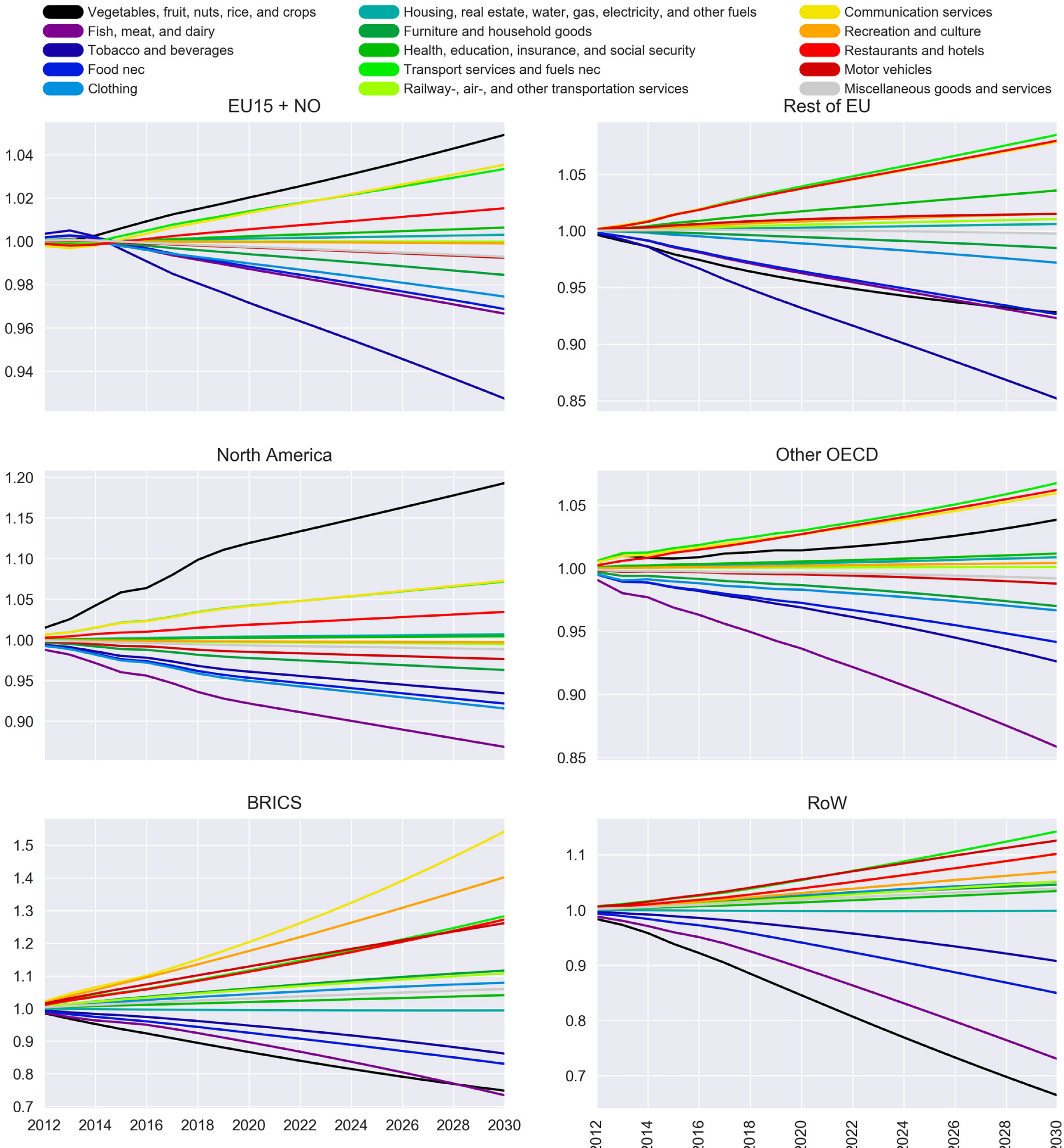

Fig. 5. Comparison of GHG emissions for the QUAIDS scenario relative to the static scenario for six regions and 15 product groups.

4.2. Limitations and future developments

The principal aim of this paper was to study the impact of income changes on consumption, and how this will translate to change in carbon footprints. To isolate this effect, we assume that economic structure and technology will not change in the future, even with respect to the changing demand from the demand system (i.e. we use Leontief production functions). It is well known that Leontief production functions are a gross simplification for modelling long-term changes in the economy, but our principal aim here is to isolate the income effect on consumption, rather than the broader economic response. In order to model the full macro-economic ramifications of demand-side and technological changes, a complete macro-economic model would be needed (e.g. GINFORS (Lutz et al., 2009) and E3ME (Barker 1999)), but it would

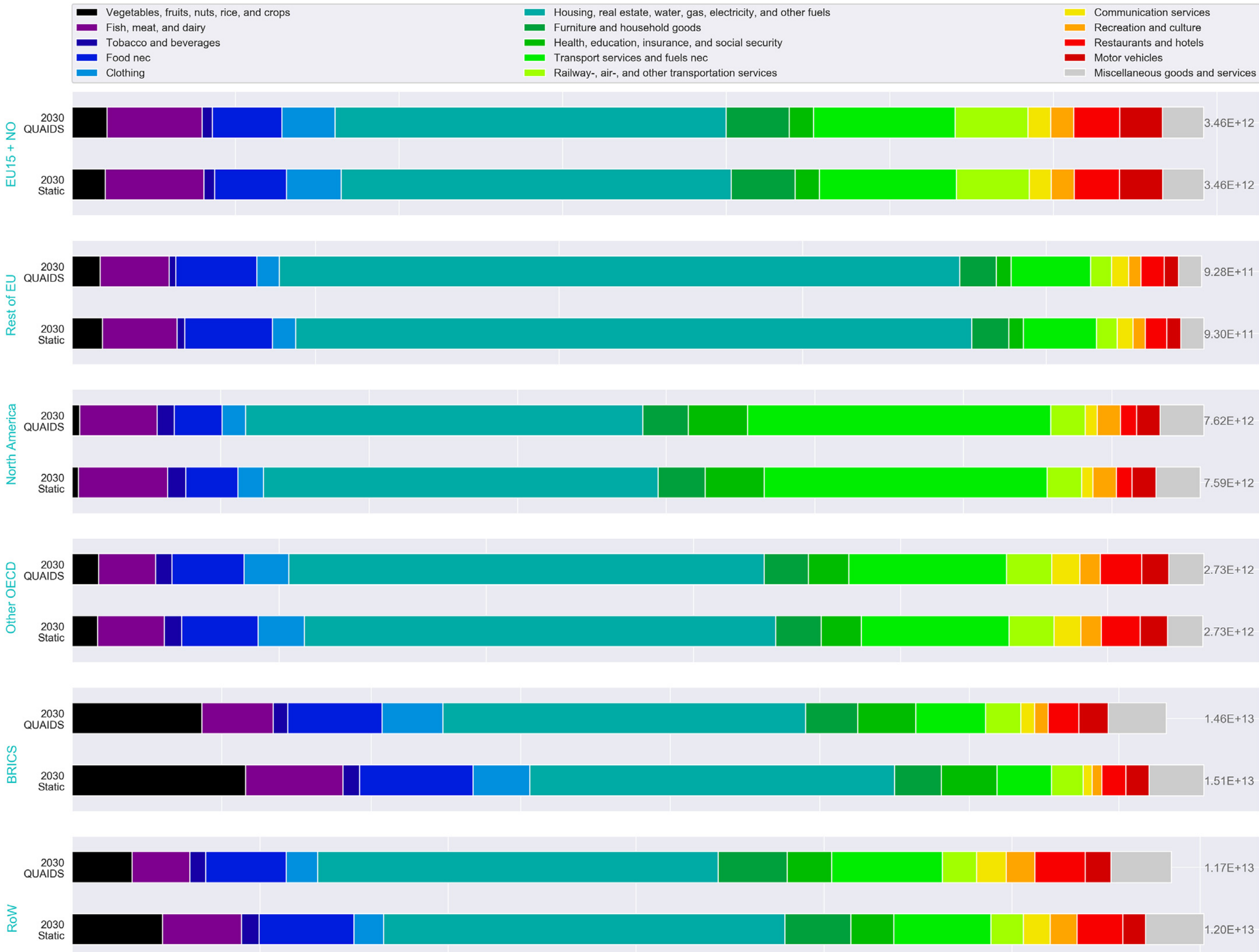

Fig. 6. Contribution to total GHG emissions for 15 product groups by six aggregate regions for the QUAIDS scenario and the static scenario.

then not be possible to isolate the income-consumption effect directly. In reality, several structural changes will occur in the economy over the time-horizon that we model, and assuming that these tend to lower the carbon intensity of production, it would be expected that Leontief multipliers based on future IO tables would be considerably lower (depending on how successful international policy is) than today.

Although it is outside the scope of our study, the price and income elasticities estimated from the demand system provide possibilities for analyses beyond what we have shown in this paper, such as to study how households distribute money saved due to efficiency gains, cheaper renewable energy or consumption changes across goods and services (Freire-González 2011, Thomas and Azevedo, 2013, Font Vivanco et al., 2014, Grabs, 2015, Chitnis and Sorrell, 2015).

For stronger analyses on income inequality, an important future improvement to the IO and the System of National Accounts framework is to add more household detail. The OECD already started this discussion (Fesseau et al., 2013, Fesseau and Mattonetti, 2013). Reconciling household budget surveys and national accounts data is challenging and a potential source of uncertainty per se (Robilliard and Robinson, 2003). However, there is still potential in adding resolution to the sector for understanding distributional issues related to the environment. This could be achieved by splitting household consumption into income quantiles as was done in Sommer and Kratena (2017). A further step could be to incorporate Social Accounting Matrices into IO models. These enable studying the complete cycle of income, from consumption to income generation and re-spending, and allow for a better understanding of the interactions between social and environmental aspects (Lenzen and Schaeffer, 2004).

At least two points are relevant to discuss in relation to the projection of future household expenditure. First, we assume that a change in income is equivalent to a change in expenditure, implicitly assuming household saving patterns are similar in the projections as in 2011. The consumption-savings decision has been frequently discussed in the demand system literature (see e.g. Lluch (1973)) and is something that could be explored further. However, as we are not analyzing different types of consumers, but rather the average consumer in each region over time, it is reasonable to assume that over the time period (2011–2030) income and expenditure are similar, although they might differ from one year to the next. Second, when projecting expenditure from diverse regions, there are likely to be inter-regional differences in terms of collective service provision and governmental spending. Countries with provision of social services would likely require lower household spending. This in turn can affect the projected expenditure as an observed lower preference for a good with rising household income can be the result of increased provision of social services rather than decreased preference for that good. This is particularly a concern when using time series data, as governmental policies regarding social services likely changes with time.

Table 4
Policy recommendations for six regions based on the 2030 projections from the QUAIDS scenario.

	Vegetables, fruit, nuts, rice, and crops	Fish, meat, and dairy	Tobacco and beverages	Food nec	Clothing	Housing, real estate, water, gas, electricity, and other fuels	Furniture and household goods	Health, education, insurance, and social security	Transport services and fuels nec	Railway-, air-, and other transportation services	Communication services	Recreation and culture	Restaurants and hotels	Motor vehicles	Miscellaneous goods and services
EU15 + NO															
CF share	- -	+	- - -	-	-	+++	-	- -	++	-	- -	- -	-	-	-
CF intensity	+	+	-	+	+	+	+	- -	+++	+	- -	- -	- -	-	- -
Demand pc	+	+	-	+	+	+	+	+	+	+	+	+	+	+	+
Rest of EU															
CF share	- -	-	- - -	+	- -	+++	- -	- - -	-	- -	- - -	- - -	- -	- - -	- -
CF intensity	+	+	-	+	-	+++	-	- -	+++	-	- -	- -	- -	- -	- -
Demand pc	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
North America															
CF share	- - -	+	- - -	-	- -	+++	-	-	+++	- -	- - -	- -	- - -	- -	-
CF intensity	- -	+++	- -	-	-	-	-	- - -	+++	+	- - -	- -	- - -	- -	- - -
Demand pc	++	+	+	+	+	++	+	++	++	++	++	++	++	++	++
Other OECD															
CF share	- -	-	- -	+	-	+++	-	-	+++	-	- -	- -	- -	- -	-
CF intensity	+	++	-	+	+	+	+	- -	+++	-	- -	- -	- - -	-	- -
Demand pc	+	-	-	+	+	+	+	+	+	+	+	+	-	-	+
BRICS															
CF share	++	++	- - -	+	-	+++	-	-	-	- -	- - -	- - -	- -	- -	-
CF intensity	++	++	-	+	-	+++	+	- -	++	-	-	- -	- -	-	- -
Demand pc	+++	+	++	++	+++	+++	+++	+++	+++	+++	+++	++	+++	+++	+++
RoW															
CF share	+	+	- - -	+	- -	+++	-	-	+	- -	- -	- -	-	- -	-
CF intensity	++	++	-	+	-	++	+	- -	+++	-	- -	-	- -	- -	- -
Demand pc	++	++	++	++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++	+++

The + and – symbols represent the relative difference compared to a baseline. For the GHG share, the baseline is the emissions share for an average product group in 2012, which is compared to the emission shares of the other product groups in 2012. The GHG intensity baseline is the emission intensity (kg CO^2-eq) per monetary unit of an average product group in 2012, which is compared to the GHG intensity of the other product groups in 2012. For the demand per capita, the baseline is 2012, and this is compared to the 2030 per capita demand. The signs correspond to the following relative changes compared to the baseline:
-, 50–100%
- - , 25–50%
- - -, 0–25%
+, 0–50% increase
+ +, 50–100% increase
+ + + larger than 100% increase

We aggregate the sectors of EXIOBASE into 15 product groups. The reasoning behind this is discussed in Section 2.1. Another reason relates to the underlying MRIO data. Creating an MRIO database involves making assumption, and balancing and interpolating data, particularly for the RoW regions where data availability is limited. Thus, MRIO household expenditure data necessarily deviates from actual expenditure data. By aggregating household expenditure to the level chosen in this paper, we avoid jumps in data points from year to year that could be a result of these mechanisms.

There is a variety of ways to forecast future consumption, all of which come with a set of limitations and assumptions. Beside the challenges related to using household consumption data from IO models, there are limitations related to the demand model used in this paper. Demand models assume homogenous, non-interacting and rational consumers, a criticism of neoclassical economic models in general (Axtell et al., 2001, Veblen 1898, Colander et al., 2004). A possible way to overcome this is to include elements of e.g. agent-based modelling (ABM). In ABM, these limitations are overcome by letting individual, autonomous agents interact. These interactions are determined on the basis of the agents' states and rules of behavior (Axtell 2000), which can for example be based on microdata from consumer expenditure surveys. This approach also enables the inclusion of consumers taking environmental considerations into their consumption decisions.

5. Conclusion

In this work we looked at the specific contribution that the income effect will have on global GHG emissions, everything else being equal.

We forecasted household consumption to 2030 in two different scenarios based on expenditure data from an MRIO database (EXIOBASE) in the period 1995–2011. In the first static scenario, consumption is forecasted using the 2011 household consumption shares of 15 aggregated product groups. In the second (QUAIDS) scenario, we use a demand system to incorporate changes in household preferences as their income changes. By applying population and GDP per capita projections, we compare the resulting GHG emissions up until 2030 to isolate the effect of income changes. Globally, we find a small 1% reduction in cumulative GHG emissions of the QUAIDS scenario compared to the static scenario. This result is mainly driven by lower emissions in the BRICS and rest-of-the-world regions. On a product level, we find lower emissions from particularly food product groups in developing countries, while emissions related to transport and services contribute to higher emissions in the QUAIDS scenario.

To further develop MRIO databases as a tool for studying future emissions from household consumption, we call for two areas of improvement. The first is a disaggregation of the household consumption vector, at least into income quantiles, which would facilitate analyses of income inequality as well as the distributional effects of the implementation of policy instruments such as environmental taxation. The second relates to disaggregation of sectors and regions. A greater detail of household consumption-relevant sectors, such as food and transport would improve the representation of household preferences in demand system analyses. A disaggregation of regions would reduce uncertainty in emissions embodied in traded goods due to high variability in GHG emission intensities among different countries aggregated in the same region.

Although there is a slight optimism in lower emissions when considering household preferences as income changes, the overall effect is limited. As a guide to policy makers we provide focal areas to reduce emissions from household consumption for 49 regions. Given that the ease of decarbonization highly differs between sectors, such a guide can be an important tool in the undoubtedly challenging decision-making faced with mitigating emission in the years to come.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105114.

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