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The association between the carbon footprint and the socio-economic characteristics of Belgian households

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Abstract

Understanding the demand-side drivers and the distribution of greenhouse gas emissions is key to designing fair and effective environmental policies. In this study, we quantify the relationship between the carbon footprint of consumption and socio-economic characteristics of Belgian households. We use a dataset that combines household-level consumption data with an environmentally extended input-output model which quantifies the greenhouse gas emissions embedded in the supply chain of goods and services that households consume. We find that income and household size are the most important determinants of household consumption-related emissions. We also find that emission intensity of household consumption in the lower part of the income distribution is higher than that of richer households because poorer households spend a higher share on emissions intensive products, especially energy.

Keywords

household carbon footprints; consumption-based emission accounting; emission distribution

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1. Introduction

It is widely acknowledged that the reduction of greenhouse gas (GHG) emissions is crucial to mitigate anthropogenic global warming. Years of negotiations have led to the landmark Paris Agreement, setting national level GHG emission reduction targets, based on where production and emissions take place. However, the geographic separation of production and consumption implies that a large share of emissions embedded in consumption take place in a country different from where the goods are produced (Davis & Caldeira, 2010). Several researchers argue that while much attention has been paid to end-use efficiency and techno-economic solutions on the production side, the perspective of the consumer, i.e. the household side, has received less attention both in research and in policy design (Creutzig et al., 2018).

There are at least two reasons for studying the relation between household characteristics and GHG emissions by households, also called the household carbon footprint (HCF). First, a better understanding of household characteristics associated with emissions will help to identify behavioural patterns and household groups to be targeted by carbon mitigation policies (Tukker et al., 2010). Besides supply-side climate policy for technological innovation and efficiency, demand-side policies may be equally necessary to dis/encourage harmful/beneficial types of consumption, for instance with regard to the energy source used for heating the dwelling, red meat consumption and emission-intensive private transport vs. the use of public transport (Vita et al., 2019; Wood et al., 2018). Second, climate change mitigation policies can have significant redistributive effects, potentially hitting vulnerable groups hard and redirecting resources to higher-income groups (Büchs et al., 2011). This can be problematic from the point of view of principles of fairness but may also result in lower acceptability and support for climate mitigation policies. For these concerns to translate into policy design, more insight is needed into the distribution of consumption patterns and how consumption-based emissions are related to various socio-economic characteristics. This can inform policies that are both effective in terms of reducing emissions and equitable with respect to their redistributive effects. Therefore, in this paper, we inquire into the household characteristics associated with GHG emissions at the household level, taking both direct and indirect emissions into account. We focus on Belgium, a rich country with a relatively high level of overall social expenditures (28.9% of GDP, including cash and in-kind benefits, excluding expenditure on education, see OECD, 2019), a moderate level of income inequality (with a Gini coefficient of 0.264, see OECD, 2019), and with 15.59 tCO₂/capita a relatively high level of consumption-based CO₂ emissions per capita (Ritchie & Roser, 2018).

The associations between HCFs and household characteristics are treated in the literature from different angles. HCFs have been investigated in relation to e.g. household size, education, time use, housing situation, yet most attention has been paid to the role of household income (Zhang et al., 2015), with broad consensus on its positive association with HCFs (see e.g. Büchs & Schnepf (2013), Girod & de Haan, (2010), Gough et al. (2011), Isaksen & Narbel (2017), Ivanova et al. (2017), Lenzen et al., (2006), Steen-Olsen et al. (2016)). Even though this positive relationship has been documented for many countries, the strength and functional form of the relationship remains unclear. While for most countries the relation between income and emissions is found to be less than proportional (Ala-Mantila et al., 2014; Büchs & Schnepf, 2013; Girod & de Haan, 2010), there is evidence for a larger than proportionate increase of emissions to income for Norway (Steen-Olsen et al., 2016) and Brazil (Lenzen et al., 2006). On the role of other factors, such as location of the dwelling (e.g. urban vs. rural; Ala-Mantila et al., 2014) and age of the main income provider (e.g. Lenzen et al., 2006), the evidence is less univocal, with patterns changing according to consumption category and country context. Only a few multivariate studies look into the relation between household socio-economic characteristics and GHG emissions by consumption category (Ala-Mantila et al., 2014 and 2016; Büchs & Schnepf, 2013; Gough et al., 2011; Ivanova et al., 2017) while the possibly different associations between different categories of consumption and household

characteristics are essential to understand the source of different levels of emissions between households, and the potential distributive effects of demand-side climate mitigation policies. This constitutes an important area for further research, especially if governments want to target certain (carbon intensive) consumption categories.

In this paper, we analyse the distribution and determinants of emissions embedded in total household consumption and in each of the following five consumption categories: food and drinks, energy and housing, transport, goods, and services. We depict the bivariate relation between a household's income and GHG emissions and make use of a multiple regression framework that we apply to each consumption category for a representative sample of households in Belgium, a country with very limited evidence on the socio-economic distribution of HCFs. Making use of the disaggregated level of our data, we also provide more detail for specific consumption categories within the categories of housing and transport. We describe the data and methods in Section 2, and present results in Section 3. In Section 4, we compare our findings with those from other studies and countries and discuss the implications. Section 5 concludes.

2. Data and methods

We use a database that consists of household level expenditure and emission data, for a representative sample of households living in Belgium, called PEACH2AIR (Cooreman et al., 2019; Frère et al., 2018). The PEACH2AIR database is based on the Belgian Household Budget Survey (HBS), enriched with information about direct and indirect emissions related to the different consumption categories and assessed over a reference period of one year (2014). We discuss here the two building blocks of the PEACH2AIR database: the HBS, and the emission data. More details on the sample design, data limitations, and imputations are available in the Supplementary Material.

2.1. Household Budget Survey

The 2014 HBS contains detailed information on socio-economic characteristics and consumption expenditures for a nationally representative sample of 6,135 Belgian private households (16,093 individuals). Since 2012, the Belgian HBS is a subsample of the Labour Force Survey (LFS). The LFS is a two-stage stratified sample. We take account of the sample design when estimating standard errors and confidence intervals (Heeringa et al., 2010), and all results are based on the weighted sample. The weights correct for unequal probabilities of selection and non-response and are calibrated at the household level to population totals.

The HBS data are likely to be subject to survey-related limitations such as insufficient coverage of the tails of the distribution (poorest and richest households) and possible underreporting of expenses. First, demonstrable underreporting regards (a) the consumption of socially less desirable goods such as tobacco or alcohol and (b) specifically for Belgium, fuel consumption for car driving. While we expect a relatively low environmental impact from the former, the latter requires specific attention. In Belgium, over 15% of passenger car use takes place in cars provided by the employer that can be used for private purposes (called company cars). Often, also fuel costs are covered by the employer, and are therefore not or only partially recorded in the HBS. As we want to gain more insight into GHG emissions by households, we imputed fuel expenses for households with a company car by making use of a Heckman selection model. Second, 4,522 households report gas and electricity expenses jointly, without making a distinction between the two. These were split into a separate 'gas' and 'electricity' component through a regression model, carried out by STATBEL, Belgium's national statistical office and provider of the data. Third, infrequent expenditures,

e.g. on durable goods or holidays, pose the challenge of discrepancy between the lifetime (or purchase frequency) of these goods and services and the timeframe of the survey. For the purpose of calculating the HCF, we smoothed infrequent expenses over household clusters by redistributing the total annual cluster-level expenses on each category equally among the households within each of the 14 clusters.

In the HBS, expenditures are categorized according to the Classification Of Individual COnsumption by Purpose (COICOP), the international reference classification for household expenditures. It provides a very detailed classification of all consumption products, with 1154 categories for Belgium (12 first level groups, broken down into more detailed 2nd, 3rd, and 4th level subgroups). For the presentation of the results we use five broad consumption categories: Food & drinks (as bought in shops); Energy & housing (all energy bills plus ‘works carried out in the house’, excluding actual construction); Transport (public and private transport, including flights, and expenses related to vehicle purchase, usage, maintenance and fuel); Goods (tangible products such as clothes, furniture, pharmacy products); Services (e.g. education, health services, banking, leisure activities, travel organised by travel agencies). More details on the grouping of consumption items, a detailed variable description and summary statistics can be found in the Supplementary Material.

2.2. Emission coefficients

The second building block of the PEACH2AIR database is emission data related to household consumption, estimated by the Federal Planning Bureau of Belgium (Frère et al., 2018). We employ emission coefficients that express ton of CO₂ equivalent emissions per euro spent on each product category, to convert HBS’ consumption expenditures into an estimate of associated GHG emissions. The household carbon footprint is the sum of a household’s direct and indirect emissions. Direct emissions stem from the burning of fossil fuels by households, for instance, when driving a car or heating the home. Direct emission coefficients are calculated for transport fuels using COPERT (a European road transport emission inventory model), and those for fuels for domestic energy are based on the Belgian national emissions inventory 2017 (see Cooreman et al. 2019 for more details). Indirect emissions are embedded in the supply chain and waste management, and refer to the emissions during the extraction of raw materials, production of intermediary products, transportation of products, and other processes that lead to the creation of the final product as well as emissions resulting from handling its disposal after use.

Indirect emission coefficients are calculated on the basis of Input-Output accounting. Emission coefficients are produced for 354 product categories, classified in accordance with the Supply and Use Tables (SUT) classification. As the input-output tables work with basic prices (rather than consumer prices) in 2010, the emission coefficients are adjusted for inflation (2010 to 2014), for product nomenclature (SUT to COICOP), and converted from basic prices to purchaser’s prices, taking account of excise duties and value added tax (see Frère et al. 2018 for more details). Eventually, the total HCF of each household, e^{tot} , is given by multiplying their expenditures on each product category i (exp_i) with the direct (e_i^{dir}) and indirect (e_i^{ind}) emission coefficients of the product category and then summing this up for all product categories (n):

$$e^{tot} = \sum_{i=1}^n exp_i (e_i^{ind} + e_i^{dir}) \quad (1)$$

EE-IO methodology has both strengths (e.g. encompassing the entire economy, avoiding double counting, capturing secondary, processed products) and weaknesses (e.g. the assumed homogeneity of produced goods in each industry, and a linear relation between price and emissions, the dependency on accurate data

collection, standardisation and environmental impact assessment). For an in-depth discussion, we refer to Kitzes (2013), Wiedmann (2009) and Steen-Olsen et al. (2016).

The EE-IO model used to construct the PEACH2AIR database is a *single region* EE-IO model developed specifically for the Belgian economy. As we only focus on Belgium, this model has the important advantage of producing emission coefficients at a relatively detailed industry and product level compared to available multi-regional models. However, it assumes that the production technology of imported goods is the same as that of the same product produced in Belgium.

Finally, two limitations arise when the HBS-data are coupled with the emission coefficients. First, the impact of housing construction is left out of scope because of insufficient information in the HBS. This implies that we could not attribute any emissions to expenses for rent, mortgages, dwelling purchases or big home renovations. Second, there are also emissions related to consumption of publicly provided services, such as education, health care or urban planning. Although their indirect emission coefficients are calculated and included, their emissions will only appear in our model if related expenditures are reported in the HBS. As these services are usually provided free of charge or at a reduced cost, we expect an underestimation as well as some bias in the distribution of emissions caused by provision of public goods and services, depending on how their use is allocated over households.

2.3. Regression analysis

We analyse determinants of the total HCF in a regression framework. We do not aim to identify causal relationships, but rather to disentangle and explore the empirical associations between the HCF on the one hand and income and other socio-economic characteristics of households on the other (see also Ala-Mantila et al., 2016; Ivanova et al., 2017). We measure HCFs at the household level and not on an individual basis because (a) the unit of observation for measuring expenditures in the HBS is the household, and not the individuals therein; (b) with the available data it is not straightforward to assign expenditures and emissions to individual members in the household (cf. Gough et al., 2011, p 34). In the bivariate analysis we present both per capita and total amounts per household, while in the regression analysis we use total HCFs. Our choice of variables to include in the multiple regression models is driven by the existing literature and data availability. Our regression model takes the following form:

$$\ln(e_i^{tot}) = \alpha + \beta \ln(inc_i) + \delta_i v_i + \gamma_i z_i + u_i \quad (2)$$

where e_i^{tot} is the total HCF from equation (1) - i.e. the GHG emissions related to yearly consumption of household i and measured in tons of CO₂ equivalents, inc_i the yearly household disposable income of household i , v_i a vector of socio-economic variables of household i (or, in case of individual-level variables, its reference person, defined as the main income provider): number of adults, number of children, age and age square, professional status, highest educational attainment, region, tenure status), z_i a vector of dwelling-related variables (number of rooms, dwelling type). α , β , δ_i and γ_i are parameter (vectors) to be estimated.³ Following Ala-Mantila et al. (2014) and Büchs and Schnepf (2013), we use dummy variables for the number of adults and children in the household, because it allows for most flexibility, implying that

³ We estimated the model by weighted least squares method with the statistical software Stata and used the ‘svy’ prefix to take into account survey design to estimate correct standard errors.

the association between the HCF and having an additional household member can vary at different household sizes, and can differ between children and adults.

There is no theoretical model that *a priori* suggests the functional form between income and emissions at the household level (Levinson & O'Brien, 2019). Brännlund & Ghalwash (2008) show that a positive and linear relationship requires very specific assumptions about preferences and the consumption-emission link, which are unlikely to be fulfilled in practice. It is an empirical question to assess which functional form (i.e. slope and curvature of the income-emission relationship) fits best the data at hand. We tested five functional forms that have been used in the literature and assessed their performance in fitting the data (Isaksen & Narbel, 2017; Weber & Matthews, 2008). We present here results for the log-log specification. With this specification, the regression coefficient for income can be interpreted as the income elasticity of emissions, i.e. the percentage change in emissions that is associated with a 1% increase in income when comparing between households with different levels of income. We estimate the regression for total emissions and for five consumption categories separately (food, energy and housing, transport, goods, and services) as well as for more detailed categories within the categories 'Energy & housing' (energy consumption in the dwelling; other housing expenditures) and 'Transport' (private motorized transport, train, and local public transport by bus, metro, or tram). We tested for the presence of multicollinearity by calculating variance inflation factors. All factors remained below 10, suggesting no evidence for multicollinearity (Wooldridge, 2009, p.99).

We perform dominance analysis to determine the relative importance of each explanatory variable in explaining the outcome variable. This method offers insight into the relative importance of the determinants for understanding the variance in the HCF. While the multiple regression model is suitable for determining the strength and direction of the association between the explanatory variables and the outcome variable, it is not suitable for ordering the explanatory variables based on their importance in explaining the outcome variable. Dominance analysis is a method that establishes variable importance by decomposing the general fit statistic, R-squared, into contributions from each of the explanatory variables. The method starts with defining all possible subsets of the predictors and calculating R-squared for each of them. Then the additional contribution of each predictor to each subset model is calculated. The additional contribution of a predictor is defined by the increase in R-squared that results from adding the predictor to a regression model that does not include the predictor. Finally, these additional contributions are summarized for each predictor by taking the average contributions to all subset models of each model size (where model size is defined as the number of predictors included in the subset model), and then averaging these conditional values. A predictor generally dominates another predictor if its averaged additional contribution is higher. For a more detailed discussion of the method, we refer to Azen & Budescu (2003) and Luchman (2015).

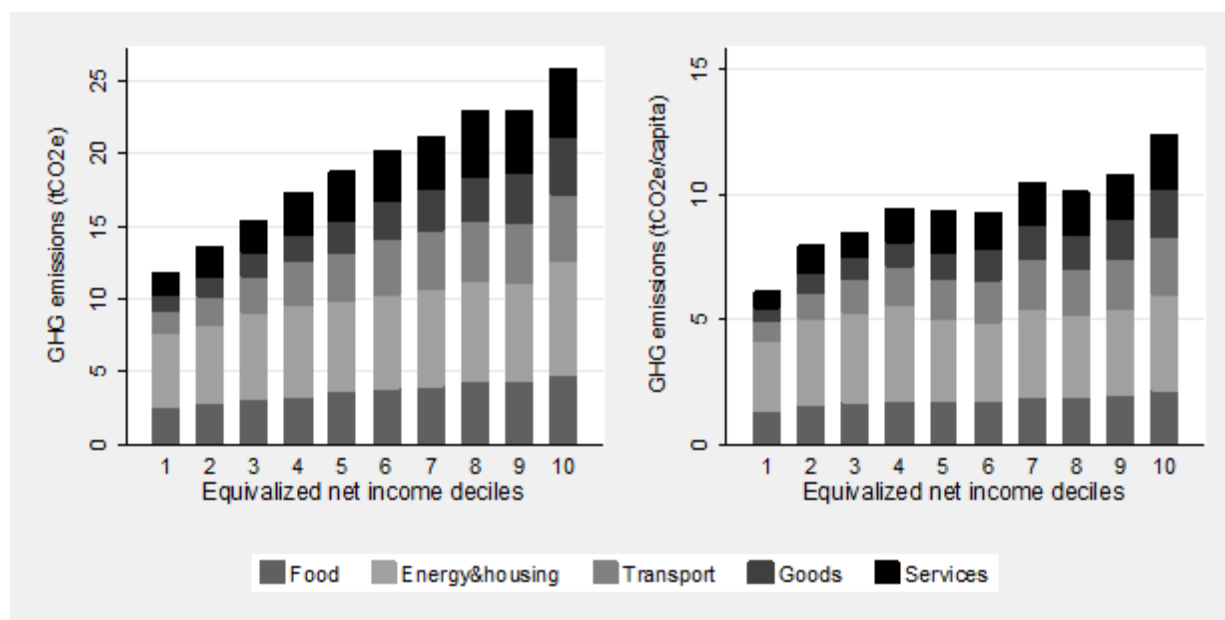
3. Results

3.1. Distribution of Belgian HCFs

There is a positive association between household income and emissions: households with higher incomes have higher emissions (Figure 1). As household size varies across the income distribution, we present both household (left) and per capita (right) emissions. Household (per capita) HCFs grow from 11.8 (6.1) to 25.8 (12.4) tons of CO₂e when moving from the lowest to the highest income decile. The composition of emissions varies across the income distribution. Emissions from 'Food' and 'Energy & housing' make up 65 (68) percent of emissions in the first decile at the household (per capita) level, while their share decreases with income and drops under 50 percent in deciles 8 to 10. Conversely, emissions from 'Transport', 'Goods'

and ‘Services’ make up 52 percent of the HCFs at the top of the distribution whereas their share is about 35 (32) percent at the bottom.

Figure 1. Distribution of household (left) and per capita (right) Belgian HCFs over income deciles.



Note: Deciles are constructed by equivalising income using the modified OECD equivalence scale, which assigns the value of 1 to the first adult, 0.5 to each additional adult and 0.3 to each child (defined as a person younger than 14). The weighted sample of households is used for identifying the income deciles.

Source: PEACH2AIR database, authors' computations.

While absolute emissions are higher at the top of the income distribution, the emission intensity of consumption is lower towards the top compared to the bottom (Figure 2). Emission intensity exhibits a steady decrease from the bottom to the top of the distribution from 802 to 616 gCO₂e/euro. This is due to the different consumption bundle compositions at the top and the bottom of the distribution, and differences in emission intensities of consumption categories: the mean emission intensity of products in the ‘Energy & housing’ category is more than ten times higher (3809 gCO₂e/euro) than in the ‘Goods’ category (306 gCO₂e/euro). The differences in consumption bundle composition, with low-income households spending a higher share of their income on emission-intensive ‘Energy & housing’ consumption, translate into a pattern of decreasing emission intensity with increasing income.

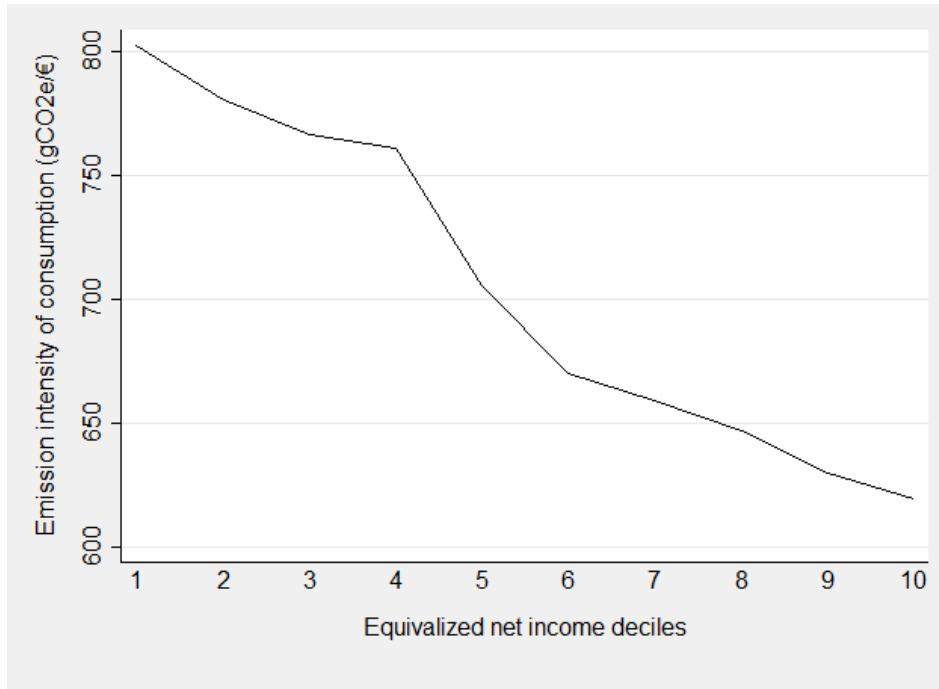


Figure 2. Emission intensity over income distribution.

Source: PEACH2AIR database, authors' computations.

Note: We calculate the emissions intensity of the consumption bundle of each household by dividing their total HCF with their total expenditures and compute the average of these values within each income decile. Income is equivalized with the modified OECD equivalence scale.

3.2 Regression models and dominance analysis

We now present the results of the multiple regression (Table 1) and the dominance analyses (Table 2). We estimate the extended model both for total emissions, and separately for emissions by expenditure category. The R-squared of the regression models ranges between 0.62 for the consumption of goods, and 0.14 for local public transport, and is equal to 0.58 for total emissions.

Table 1. OLS regression results of the natural logarithm of household GHG emissions in tons by consumption category

	Total household carbon footprint	Main consumption categories					Detail for Energy & Housing categories		Detail for Transport categories		
		Food	Energy, housing	Transport	Goods	Services	Energy	Other housing	Train	Metro, tram, bus	Fuel
Log income	0.320***	0.232***	0.115***	0.577***	0.691***	0.579***	0.099***	0.445***	0.729***	-0.173	0.177***
Number of adults (Ref.= 1)											
2	0.210***	0.450***	0.106***	0.393***	0.213***	0.186***	0.108***	0.287***	-0.176***	0.165	0.141***
3	0.265***	0.576***	0.151***	0.303***	0.127***	0.238***	0.160***	0.338***	-0.064	0.554**	0.178***
>=4	0.353***	0.738***	0.196***	0.274***	0.139***	0.382***	0.208***	0.423***	0.019	0.439*	0.174***
Number of children (Ref.= 0)											
1	0.094***	0.121***	0.070**	-0.045	-0.020	0.266***	0.083**	0.097***	-0.292***	0.129	0.007
2	0.119***	0.224***	-0.009	-0.101*	-0.069***	0.437***	0.005	0.170***	-0.175**	0.216	0.052
3	0.183***	0.312***	0.048	-0.131	-0.091**	0.623***	0.042	0.227***	-0.060	0.396	0.097
>=4	0.273***	0.399***	0.112	0.067	0.049	0.703***	0.087	0.330***	-0.445***	0.019	0.239*
Age of reference person	0.018***	0.027***	0.004	0.039***	0.013**	0.024***	0.004	0.026***	0.006	0.006	0.035***
Square of age	-0.000***	-0.000***	0.000	-0.000***	-0.000**	-0.000*	0.000	-0.000***	-0.000	0.000	-0.000***
Professional status of reference person (Ref.= working)											
unemployed	-0.086**	-0.087	0.022	-0.415***	-0.199***	-0.248***	-0.009	-0.174***	0.138	-0.215	-0.162*
student	-0.019	-0.061	-0.029	-0.221	-0.063	0.150	-0.001	-0.107	0.537	-0.798*	-0.520
homemaker	-0.019	-0.093	0.050	-0.148	-0.073	-0.166	0.022	-0.084	-0.041	-0.587*	-0.060
incapacitated	-0.049	0.004	0.049	-0.421***	-0.071	-0.067	0.045	-0.109***	0.035	-0.396	-0.171*
pension	0.006	0.044	-0.008	0.020	0.051	0.015	-0.027	0.016	0.016	-0.452*	0.017
Education reference person (Ref.= <=lower secondary)											
upper secondary	0.072**	0.052*	0.038	0.214***	0.095***	0.243***	0.029	0.127***	0.068	0.059	0.086
tertiary or more	0.157***	0.162***	0.056	0.284***	0.225***	0.460***	0.044	0.250***	0.418***	-0.073	0.146***
Region (Ref.= Flanders)											
Brussels	-0.022	0.030	0.017	-0.176*	-0.036	-0.080	-0.012	-0.033	0.074	0.803***	-0.169***
Wallonia	0.078***	0.016	0.214***	0.142***	-0.019	-0.188***	0.218***	-0.002	-0.119**	0.517***	0.105***

	Total household carbon footprint	Main consumption categories					Detail for Energy & Housing categories		Detail for Transport categories		
		Food	Energy, housing	Transport	Goods	Services	Energy	Other housing	Train	Metro, tram, bus	Fuel
Tenure status (Ref.= owner)											
Tenant	-0.107***	-0.047*	-0.062*	-0.235***	-0.112***	-0.313***	-0.002	-0.134***	0.062	0.001	-0.122***
Number of rooms (Ref.= 1)											
2	0.185***	0.174**	0.107	0.171	0.114	0.362***	0.090	0.247***	0.040	0.765*	0.124
3	0.252***	0.104	0.207*	0.348*	0.180**	0.474***	0.184*	0.297***	-0.309	0.394	0.159
4	0.316***	0.120	0.318***	0.446**	0.174**	0.485***	0.309***	0.322***	-0.373*	0.301	0.110
5	0.345***	0.180*	0.391***	0.418**	0.180**	0.470***	0.372***	0.328***	-0.264	0.202	0.106
>=6	0.398***	0.211**	0.472***	0.436**	0.229***	0.537***	0.461***	0.369***	-0.224	0.321	0.167
House type (Ref.= Detached)											
Semi-detached	-0.084***	-0.010	-0.136***	-0.174***	-0.013	-0.010	-0.150***	-0.043**	0.082*	0.072	-0.119***
Apartment	-0.160***	-0.066**	-0.366***	-0.256***	-0.067*	0.143**	-0.445***	-0.058*	0.247**	0.120	-0.107*
Other	-0.020	-0.061	-0.116	-0.157	0.151	0.168	-0.131	0.016	0.018	0.657	0.007
Constant	-1.573***	-2.791***	-0.150	-6.634***	-7.189***	-7.138***	-0.041	-3.642***	-12.512***	-2.799*	-1.856***
Observations	6125	6125	6125	6125	6125	6125	6125	6125	5942	903	4677
R ²	0.582	0.488	0.265	0.415	0.621	0.355	0.256	0.595	0.155	0.145	0.173

Notes: For the categorical control variables, the reference category is included between brackets. Standard errors can be found in Supplementary Material. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Source: PEACH2AIR database, authors' computations.

Income is the most important determinant of the total HCF, accounting for 28 percent of the explained variance in total HCF (see Table 2). The coefficient of the income variable is 0.33, implying that otherwise similar households with a household income that is one percent higher have on average household GHG emissions that are 0.33 percent higher, holding other factors constant (see Table 1). Both the importance of income in the dominance analysis and the income elasticity of the HCFs vary greatly across consumption categories. While income is the most important variable in the ‘Goods’ and ‘Services’ models, accounting for 43.5 and 32.4 percent of the explained variance, respectively, its importance and coefficients are much lower in the ‘Food’ and ‘Energy and housing’ models. Breaking down emissions from housing and transport, it appears that income remains a key determinant for non-energy related housing costs, as well as for some modes of transport (most notably Train use, and to a lesser extent, Fuel). Emission categories with a low income elasticity mainly incorporate goods and services that satisfy basic needs and therefore grow much less with increasing income. Low-income households spend a proportionally higher share of their income on e.g. ‘Food’ (25% on average in the first decile) than high-income households (9% in the tenth decile), although in absolute terms, average spending per capita increases from 153€/month in the bottom decile to 267€/month in the top decile (in 2014 prices). Income elasticity is low for these categories e.g. 0.1 for ‘Energy’ and 0.23 for ‘Food’. In contrast, the emissions from the other three product categories are more income-elastic, as reflected by the higher coefficients for ‘Transport’(0.60), ‘Goods’ (0.69), and ‘Services’ (0.59). Richer households spend higher shares of their overall expenditures on these three categories (cf. Figure 1). Emissions from using local public transport (metro, tram, bus) have a negative (although not significant) income elasticity, reflecting the more widespread use of these transport modes among low-income households.

Household size is positively associated with the HCF in most models and it is the most important variable in the ‘Food’ model (see Table 2). The size of the estimated coefficients of the household size dummies varies across the models (Table 1). In the ‘Total’ model, a household with two (three) persons emit 20 (26) percent more than a single-person household, which is the reference category. The emissions of larger households are higher than those of smaller households, but with additional members HCF do not increase proportionally. As the total HCF increases only with only 20 (10) percent for the first additional adult (child), emissions per capita fall with growing household size. The coefficients for household size differ greatly according to consumption category. The estimated coefficients for extra adults are smallest in the ‘Energy and housing’ model, reflecting that an extra household member adds relatively little extra emissions from domestic energy use, and are highest in the ‘Food’ model, implying economies of scale are here the weakest. For children, emission coefficients are highest the ‘Services’ model, and, notably, negative for ‘Transport’ and ‘Goods’ models. This implies that, *ceteris paribus*, households with children are associated with slightly lower emissions from these categories when compared to households without children. This pattern is particularly pronounced for traveling by train. In all models except ‘Services’, the adult dummies have estimated coefficients that are (much) more than double of those for children, and adult dummies are two- to ninefold more important in the dominance analysis than the child dummies. Hence, children add (much) less to a household’s overall HCF than adults.

The two variables related to **characteristics of the dwelling** (number of rooms and dwelling type) emerge as the third and fourth most important variables in the dominance analysis in the ‘Total’ model, accounting for 15 and 10 percent of the explained variance, respectively. This stems from their association with domestic energy use, for which the housing-related variables have the most important explanatory power (over half of the total R-squared). The coefficient estimates of the housing-related variables in the ‘Energy and housing’ model imply that the HCFs of households living in semi-detached houses or apartments are respectively 14 and 37 percent lower than those of households living in detached houses, *ceteris paribus*. Detached houses tend to have higher heating requirements than other type of dwellings, with larger surfaces

and lower energy performance than apartments (VEA, 2019). The significant coefficients for detached and semi-detached houses in the regression model for ‘Transport’ presumably reflects increased car use due to longer commuting and other travel distances for households that live away from urban centres. In contrast, living in an apartment appears to be associated with higher emissions for transport by train compared to living in a detached dwelling, reflecting better coverage and railway access in towns and cities.

Age (i.e. age of the reference person) contributes relatively little to the explained variance in emissions. Yet, except for the use of public transport and domestic energy use, the association between age and GHG emissions is significant. In all these cases, this relationship takes the form of an inversed u-shape. The degree to which emissions change with age, and the age at which emissions peak vary considerably between consumption categories. The age-gradient of emissions seems strongest in the case of (private) transport, and weakest in the case of goods (and not significant in the case of domestic energy use and public transport). In case of total emissions, emissions from food and those from the use of services, the peak is after 65, while it is at a much younger age in the case of fuel for private transport (43 years old), transport in general (46), goods (53) and other housing expenditure (60).⁴ This might reflect the fact that values and lifestyles change with age, which translates into different consumption and emission patterns (Büchs & Schnepf, 2013; Golley & Meng, 2012).

The **professional status** variable refers to the household head, with ‘working’ as reference category. Its contribution to the explained variance in emissions is relatively modest, except for emissions from (private) transport. While there is no significant relationship with emissions from food and domestic energy use, the conditional gap in emissions between households with a working reference person and those with an unemployed or incapacitated reference person is particularly wide for transport (42%), with gaps half that size for emissions from ‘Goods’ and ‘Services’ in households with an unemployed head. For these categories no significant differences are found for households with an incapacitated reference person compared to a working head). Given that income is controlled for, these patterns may be driven by more unobserved characteristics such as wealth and expectations regarding future income.

The higher the **educational attainment** of the household’s reference person, the higher the household’s emissions. The education-emissions association is strongest in the regression results for ‘Services’, where a household with tertiary education is associated with 46 percent higher emissions than the reference category (‘primary or less’) controlling for other characteristics. This may be driven by different preferences, norms and values related to how to spend their free time, translating into more (longer educated) or less (shorter educated) emission-intensive consumption. It may also capture access to other economic resources (including wealth). Further research could investigate the exact driving forces behind the positive education-emissions relationship. Also in the case of emissions from transport education is an important factor, with households with a higher educated reference person are associated with a 28 percent higher footprint. The additional detail for the different transport categories shows that tertiary education is associated both with higher private fuel emissions (+15% compared to the reference category) and higher train-related emissions (+42%). This higher footprint among tertiary educated can be expected to relate to mobility for both leisure and employment purposes.

The lowest level of geographical disaggregation in the data is **region**. Belgium has three regions: the highly urbanized Brussels-Capital Region (BXL), the relatively more rural Walloon Region (WL) and the predominantly suburban region of Flanders (FL) (reference category in the regression). Table 1 shows that, when controlling for other characteristics, households in Wallonia emit about 8 percent more than those in

⁴ The graphical plots for the predicted relationships can be found in the Supplementary Material.

Flanders. This pattern seems to be mainly driven by emissions from domestic energy use and ‘Transport’, while emissions from services appear to be considerably higher in Flanders as compared to Wallonia. Houses in Wallonia are older and emission-intensive types of heating, coal, fuel oil and wood, are more prevalent. Additionally, travel, commuting, and driving distances are longer in Wallonia than in Brussels and Flanders (Verhetsel et al., 2009). Region is the dominant contributing factor in the explained variance of emissions from local public transport, with considerably higher emissions from this category in Brussels and Wallonia compared to Flanders.

Tenure status is a dummy variable, that distinguishes between owners and tenants. We find that the HCFs of tenants is less than the HCFs of owners. The difference is the biggest in the ‘Transport’ and ‘Services’ models, where tenants emit respectively 24 and 31 percent less than owners, *ceteris paribus*. While there are more tenants in densely populated areas, explaining lower emissions for transport, the lower emissions for services suggest that also other unobserved factors may be at play, again including wealth and income insecurity.

Table 2. Results of dominance analysis.

	Total	Main consumption categories					Detail for Energy and Housing		Detail for transport		
		Food	Energy & housing	Transport	Goods	Services	Energy	Other Housing	Train	Metro Tram Bus	Fuel
Income	28.5	24.7	10.2	29.4	43.5	32.4	8.6	33.8	38.6	1.4	23.0
Number of adults	20.0	35.7	10.9	17.2	16.6	14.1	10.5	21.3	7.7	10.2	13.7
Number of children	3.9	5.0	1.4	1.9	1.8	8.4	1.4	4.4	2.7	3.8	5.4
Age	1.2	4.0	3.4	0.8	0.4	1.0	3.5	0.8	5.0	2.6	7.2
Professional status	5.6	4.8	2.4	11.3	8.8	7.7	2.3	7.7	7.9	8.3	15.5
Education	6.3	4.9	1.4	7.6	9.6	12.7	1.0	8.8	23.7	1.8	9.1
Region	2.0	0.5	11.8	3.0	0.9	2.9	12.7	0.9	3.6	48.7	5.6
Tenure status	8.2	4.7	9.0	9.0	6.1	9.2	7.0	7.1	0.6	2.2	6.5
Number of rooms	14.1	9.8	23.7	10.5	7.7	8.5	23.6	9.7	6.9	14.7	5.7
Housing type	10.2	5.8	25.9	9.2	4.5	3.1	29.5	5.5	3.2	6.5	8.4

Note: Numbers indicate the percentage contribution of each variable to the overall fit measure (R-squared) in the regressions presented in Table 1.

Source: PEACH2AIR database, authors’ computations.

4. Discussion

We find a strong association between income and the household carbon footprint, but also that the emission intensity of consumption bundles decreases with growing income. Two factors affect this pattern: (i) the relative composition of typical consumption bundles at the bottom and the top of the income distribution, and (ii) the relative emission intensities of consumption categories compared to each other. A similar pattern has been found in the Netherlands, the UK and China (Golley & Meng, 2012; Kerkhof et al., 2009a). This negative relationship is, however, not a necessity, as is shown by the cases of Norway and Sweden, where emission intensity either increases or stays constant with growing income levels. In Sweden, the positive emission intensity-income relationship is likely to be driven by the fact that the share of domestic energy emissions does not vary considerably with income, as low-income households in apartment buildings use

low-emission intensive district heating, while high-income households in detached houses have no access to district heating (Kerkhof et al., 2009a). For Norway, Steen-Olsen et al. (2016) point to (i) the high share of hydropower in electricity generation, resulting in a relatively low energy intensity of domestic energy use and (ii) increasing energy-intensive mobility with income. These outcomes suggest that the emission intensity of the national energy supply is a key determinant of the income-energy intensity relationship.

The relationship between intra-household sharing, household scale economies and the HCF has been studied in more detail by Ala-Mantila et al. (2016), Fremstad et al. (2018), Ivanova & Büchs (2020), and Underwood & Zahran (2015). Even though our estimations are not directly comparable to these studies, we also find that there are important economies of scale for Belgian households when living together, in terms of the level of GHG emissions.

These results illustrate the various links between background characteristics and direct and indirect GHG emissions by households. Importantly, the results do not only show important inequalities in the contribution to GHG emissions, but also how these vary by consumption category. The policy implications from our study are largely indirect and specific analyses of potential measures are needed in order to quantify eventual distributional effects of measures aimed at mitigating CO₂-emissions. Nevertheless, our results allow to point to four policy implications.

First, the consumption category that is targeted determines the distributional pattern that can be expected. Any distributional implication will be vastly different whether goods and services are concerned (whose share in the consumption basket rises with income) or housing, energy & food (which decreases with income). Price policies that directly target the emissions of carbon intensive basic goods, such as food and heating, risk to hit the poor particularly hard if not accompanied by other measures. In contrast, investments in insulation of the dwellings in which the poor live, is likely to generate both environmentally and socially positive outcomes. Second, the relevance of socio-economic characteristics goes beyond merely income: several socio-economic factors are associated with emissions within specific consumption categories, even after controlling for income and household size. This may help to identify target groups of special interest for policies that aim to discourage high-emission types of consumption, as well as to identify groups that may be hit particularly hard by some measures and require accompanying policies. Conversely, it may also point to groups that risk not to gain from increased subsidies for some types of consumption (e.g. train use), unless targeted policies are put in place to encourage these types of consumption (e.g. focused on replacing car use by train use). Third, the socio-demographic trend towards smaller households puts an upward pressure on emissions (Bradbury et al., 2014), given the relatively strong economies of scale we observe in relation to household size. This is certainly a tricky issue, but given its importance for efficiently reducing GHG emissions, it seems worthwhile to reflect further on policies that could stimulate an optimal use of the gains from household economies of scale, and investigate further how decreased sharing within households could be compensated by increasing sharing between households (e.g. Fremstad et al. 2018). Fourth, the results also point to the interaction of HCFs with infrastructural configurations, and spatial planning (as illustrated by the importance of the dwelling-related and regional dimension in our results), underlining the country- or region-specificity of the findings. The relative importance of the different consumption categories in total emissions as well as the resulting distributional patterns, largely depend on national infrastructures: the spatial and transport organization, the CO₂-intensity of energy production, and the qualities of the housing stock. Considering these underlying factors is mandatory for any cross-country comparison.

As mentioned above, our results point to important factors that may help to design climate mitigation policies targeted at reducing certain types of consumption (especially CO₂-intensive types of domestic

energy or transport modes) by households, while taking into account potential adverse distributive effects. Although we are convinced that demand-side measures have an important role to play to achieve GHG emissions reductions, it should be clear that household consumption operates within a broader context on which individual households by themselves have limited direct impact. Public infrastructure, and the available incentive structure are important factors to take into consideration, along with broader supply-side measures that directly tackle energy production, land-use and emissions from industry.

5. Conclusion

In this paper we investigated which micro-level factors are associated with direct and indirect GHG emissions that result from consumption by households. Our study is the first multivariate analysis of direct and indirect GHG emissions by households living in Belgium. Using regression analysis we find that income, household size, age, education and dwelling size are significantly and positively associated with household GHG emissions, while unemployment, living in an apartment (rather than living in a house), and being a tenant are negatively associated. Income and household size stand out as the two most important explanatory variables, confirming that (a) higher income households on average have consumption patterns that lead to considerably higher emissions, although emissions rise less than proportional to income and (b) households with more members emit more in absolute terms, but less on a per capita basis, pointing to non-negligible economies of scale. An important driving factor behind both these observations is the weight of the most polluting consumption category (Energy & housing). It is the least sensitive to changes in household size and is also found to be most income-inelastic.

While our analysis offers a starting point for understanding GHG emissions by households in Belgium, more specific analyses are required for designing policies. An important expansion could be to link with longitudinal data (which unfortunately do not exist for Belgium), to gain more insight into consumption dynamics and longitudinal effects of price changes and technological change on GHG emissions. Another expansion could be to refine the computation of emission coefficients, for instance by combining the Belgian input-output tables with a multi-regional component, such that the domestic technology assumption could be weakened. While our analysis reveals the associations between the observable household characteristics, consumption patterns and GHG emissions, further research is needed on the deeper drivers of these relationships. As noted above, an important part of the environmental impact is generated via infrastructural organization of land-use, housing, mobility and energy production, and there is (at least for Belgium) relatively little research about how this interacts with the patterns that we observe. Similarly, additional data collection would be required to directly link attitudes, habits, routines, or symbolic meanings of consumption to households' observed consumption patterns (cf. Tukker et al., 2010). Insight into these dynamics is a crucial complement to deepen our understanding of how consumption patterns can evolve to more sustainable outcomes.

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