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Petra Zsuzsa Lévay, Josefine Vanhille, Tim Goedemé and Gerlinde Verbist

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Petra Zsuzsa Lévay*[1], Josefine Vanhille[1], Tim Goedemé[1,2], Gerlinde Verbist[1]

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Abstract

Understanding demand-side drivers and distribution of greenhouse gas emissions is key to design fair and efficient 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. Similar to studies in other countries, we find that emission intensity (emissions per euro of expenditures) of households at the lower part of the income distribution is higher than that of richer households because poorer households spend higher share of their expenditures on emissions intensive products, especially on energy and housing. We also find that living standards and household size are the most important determinants of household consumption-related emissions. The expenditure-elasticity of household emissions is less than unity, i.e. emissions increase with expenditures, but in a less than proportionate way. However, the elasticity changes when emissions from different consumption domains are analyzed. It is lowest for energy and housing and highest for services.

Keywords

household carbon footprints; Environmental Engel curves; consumption-based emission accounting; elasticity; emission distribution

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[1]: Herman Deleeck Centre for Social Policy, Department of sociology - University of Antwerp.

[2]: Institute for New Economic Thinking at the Oxford Martin School, Department of Social Policy and Intervention – University of Oxford

*: Corresponding author. E-mail: petra.levay@uantwerpen.be

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1. Introduction

It has been increasingly acknowledged that the reduction of greenhouse gas (GHG) emissions is crucial to mitigate anthropogenic global warming. Public opinion surveys show that the large majority of the population in Europe and in the US have an increased awareness about global warming and consider it a serious problem (Kantar, 2019; Leiserowitz et al., 2018; Poortinga et al., 2018). In the global climate policy arena, years of negotiations have led to the landmark Paris Agreement that aims to keep global average temperature increase well below 2 °C above pre-industrial levels (UNFCC, 2015), setting national level GHG emission reduction targets, based on where emissions take place. An intensified geographic separation of production and consumption went hand in hand with a steady increase in global inter-industry trade and growing fragmentation of production chains (Brülhart, 2008; Los, Timmer, & de Vries, 2015). As a result, a considerable amount of CO_2 is embedded in international trade, i.e. production and emissions happen in a different location compared to where consumption takes place (Davis & Caldeira, 2010; Peters & Hertwich, 2008). The question whether the producer or the consumer is responsible for emissions and how climate mitigation burdens should be shared has been subject to discussions both on the normative (Duus-Otterström & Hjorthen, 2018) and on the methodological level (Bastianoni, Pulselli, & Tiezzi, 2004; Munksgaard & Pedersen, 2001). The heightened climate change mitigation ambitions, the growing interconnectedness of global supply chains, and the emergence of the producer versus consumer responsibility discussion have brought about an increased interest and need to better understand the relationship between consumption and GHG emissions. 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 has received less attention both in research and in policy design (Creutzig et al., 2018; Mundaca, Ürge-Vorsatz, & Wilson, 2019).

At the household level, the consumption-emissions relationship is researched by calculating households' GHG or CO_2 emissions, called the household carbon footprint (HCF). The distinction between direct and indirect emissions is key in this context. Direct emissions stem e.g. from using fuel for the car or heating fuel for the home, while indirect emissions stem from the consumption of goods and services that are produced by others. Indirect emissions are embedded in the supply chain and waste management, i.e. they refer to the emissions during the extraction of raw materials, production of intermediary products, transportation of products, other processes that lead to the creation of the final product as well as emissions resulting from handling its disposal after use. We define HCF as the sum of a household's direct and indirect emissions. Indirect emissions account for the majority of HCFs (Zhang, Luo, & Skitmore, 2015). Previous research shows that only three consumption categories (housing, transport, and food) make up the lion's share of an average HCF, accounting for 70% to 80% of the HCF in industrialized countries (Büchs & Schnepf, 2013; Druckman & Jackson, 2016; Gough et al., 2011; Tukker & Jansen, 2006).

There are at least two reasons for studying the relation between household characteristics and greenhouse gas emissions by households. First of all, given that direct emissions by households account for a sizeable share of total emissions, it is important to understand why and where emissions take place to design effective and efficient policies that help to reduce these emissions to zero. A better understanding of the household characteristics associated with emissions will help to identify behavioural patterns that are crucial for effective policy design, and may also help to identify groups of households to be targeted by carbon mitigation policies (Tukker, Cohen, Hubacek, & Mont, 2010). The same argument applies to some extent to indirect emissions by households, as apart from putting in place policies to reduce emissions that occur during the production process, it may be sometimes equally important, or even more efficient and/or necessary, to also discourage or encourage certain types of consumption (Barrett & Scott, 2012; Poore & Nemecek, 2018; Wood et al., 2018). A second important reason to study HCFs is that climate change mitigation policies can have significant redistributive effects, potentially hitting vulnerable groups hard and redirecting resources to higher-income groups (Büchs, Bardsley, & Duwe, 2011). This can be problematic from the point of view of principles of fairness, but also may result in lower acceptability and support for climate mitigation policies. As a result, it is important to gain more insight into consumption patterns across the income distribution and obtain a fine-grained understanding of how consumption-based emissions are related to various socio-economic characteristics. This may help to develop 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, while taking both direct emissions and indirect emissions into account. To do so, we focus on Belgium, a rich country with a relatively high level of social expenditures and a moderate level of income inequality (e.g. OECD, 2019), and a high level of consumption-based CO_2 emissions per capita (Ritchie & Roser, 2018).

A number of studies have investigated the household characteristics that are associated with HCFs. In particular, quite some attention has been paid to the relation between household income and GHG emissions (Zhang, Luo, & Skitmore, 2015). There seems to be a consensus about the positive association between household carbon footprints and household income[3]. Even though this positive relationship has been documented for many developed countries, the strength and the functional form of the relationship (in the cross-section) remains unclear in the literature. While for most countries it has been found that, in the cross-section, the relation between income and emissions is less than proportional (Ala-Mantila, Heinonen, & Junnila, 2014; Büchs & Schnepf, 2013; Duarte, Mainar, & Sánchez-Chóliz, 2012; Girod & de Haan, 2010), there has been evidence for a larger than proportionate increase of emissions to income for Norway (Steen-Olsen, Wood, & Hertwich, 2016) and Brazil (Lenzen et al., 2006)[4].

There is less consensus regarding the role of other factors, such as the location of the dwelling (e.g. urban vs. rural) and the age of the household head. The limited number of multivariate studies impedes drawing clear conclusions about the associations between individual socio-economic variables and HCFs. More multivariate studies can advance the understanding of what kind of households are associated with different levels of emissions (Büchs & Schnepf, 2013). In particular, only a few multivariate studies look into the relation between household characteristics and GHG emissions by consumption category (Ala-Mantila et al., 2014 and 2016; Büchs & Schnepf, 2013; Gough et al., 2011; Irfany & Klasen, 2017; Ivanova et al., 2017). Nonetheless, this is an important area for further research, especially if governments want to target certain (carbon intensive) consumption categories. Therefore, in this paper, we add to the literature by analysing 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 living standard and GHG emissions, and make use of a multiple regression framework that we apply to each consumption category for a representative survey of households in Belgium. We find that while richer households tend to contribute much more to GHG emissions than poorer households, the association between some household

[3]Ala-Mantila et al. (2014), Ala-Mantila et al. (2016), Brännlund & Ghalwash (2008), Büchs & Schnepf (2013), Christis et al. (2019), Duarte et al. (2012), Fremstad, Underwood, & Zahran (2018), Girod & Haan, (2010), Golley & Meng, (2012), Gough et al. (2011), Irfany & Klasen (2017), Isaksen & Narbel (2017), Ivanova et al. (2017), Kerkhof et al. (2009), Lenzen et al., (2006), Lenzen (1998), Pohlmann & Ohlendorf (2014), Poom & Ahas (2016), Steen-Olsen et al. (2016), Weber & Matthews (2008), Wier et al. (2001).

[4] The study of Lenzen et al. (2006) measures energy requirements of households, and not the carbon footprint of households. However, the methodology and conclusions of the paper is similar to HCF studies.

characteristics (including household income) and GHG emissions varies considerably by consumption category.

The paper is structured as follows. We describe the materials and methods in Section 2. Results are presented in Section 3. We compare the findings of this study with findings for other countries and discuss the implications of our results in Section 4. Section 5 concludes.

2. Data and methods

For our analysis we use a database that consists of expenditure and emissions data on the household level, for a representative sample of households living in Belgium, called PEACH2AIR database (Cooreman et al., 2019; Frère, Vandille, & Wolff, 2018), which. 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. Expenditures and emissions of households are assessed over a reference period of one year (in our case 2014). In what follows, we discuss the two building blocks of the PEACH2AIR database: the Belgian Household Budget Survey, and the emissions data.

2.1. Household Budget Survey

The 2014 Belgian (HBS) contains detailed information on socioeconomic characteristics and consumption expenditures for a sample of 6,135 Belgian private households (16,093 individuals)[5]. The HBS is a biennial survey, and consists of a subsample of the Belgian Labour Force Survey (LFS)[6]. The LFS sample is a two-stage stratified sample from which the HBS is drawn in the third-stage. We take as much as possible account of the sample design when estimating standard errors and confidence intervals (Heeringa, West, & Berglund, 2010). The HBS micro-data are provided by Statbel, Belgium's statistical office.

Information on the responding households is collected in two ways: (1) each household has to keep a logbook of all expenditures for the duration of one month; and (2) at the end of the month follows a face-to-face interview. In the logbook, the household records all expenditures and some characteristics of the purchases made (type of expenditure, price, quantity, unit of measurement, private part of purchase, place of purchase). The questionnaire completed during the interview collects information about household composition and the socioeconomic characteristics of the household and its members (such as the average or usual monthly total household income after taxes and benefits, age, region, education, etc.), details about the dwelling (year of building, heating type, etc.), the purchase of durable goods during the previous four months, periodic expenses (e.g. television subscription) and the possession of large devices (e.g. car, laptop, washing machine).

Given the survey nature of the HBS data, the data are likely to be subject to a number of survey-related limitations such as insufficient coverage of the tails of the distribution (households with the lowest and the highest incomes) and possible underreporting of expenses. Two sources of such underreporting are: (i) the consumption of socially less desirable goods such as tobacco or alcohol (ii) and – specifically for Belgium -fuel consumption for driving a car. While we expect a relatively low environmental impact from the former, this is not the case for the latter. In Belgium, a relatively large share of car use takes place in company cars that can be used for private purposes. Often, fuel costs are covered by the employer when

[5] Households that consist exclusively of persons older than 76 are not interviewed.
[6] Before 2012 the survey was annual and separate from the LFS.

using these cars, and are therefore not 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[7]. A further limitation of the HBS is that 4522 households report gas and electricity expenses jointly, without making a distinction between the two. Therefore, Statbel (Belgium's statistical agency that provides the HBS data) developed a regression model to separate the overall energy bill into a gas component and an electricity component.

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 (one month for frequent purchases and 4 months for infrequent purchases and durables). For the purpose of calculating the HCF, we smoothed infrequent expenses over household clusters. We created 14 clusters of households of similar size and similar income level and redistributed the total annual cluster-level expenses on each category equally among the households within each cluster.[8]

In the HBS, expenditures are categorized according to the Classification Of Individual COnsumption by Purpose (COICOP), which is the international reference classification for household expenditures. It provides a very detailed classification of all consumption products into – for Belgium – 1154 categories (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 and drinks (as bought in shops); Energy and Housing (all energy bills plus 'works carried out in the house', excluding actual construction); Transport (public and private transport, including flights, and including expenses related to vehicle purchase, usage, maintenance and fuel); Goods (tangible products such as clothes, books & magazines, furniture, pharmacy products and so on); Services (education, health services, banking & insurances, leisure activities, hotels and restaurants, …). More details on the grouping of consumption items, a detailed variable description and summary statistics can be found in the annex.

2.2. Pollution coefficients

The second building block of the PEACH2AIR database is emission data related to household consumption, estimated by the Federal Planning Bureau of Belgium (Cooreman et al., 2019; Frère et al., 2018). Households emit GHG both directly (burning fuel to drive the car or heat the home) and indirectly (embodied in the supply chain of goods and services purchased by households). To calculate the emissions we employ 'pollution coefficients' that express emissions per euro spent on each product, to convert HBS' consumption expenditures into an estimate of the GHG emissions associated with them. Direct pollution coefficients are used in the case of transport fuels[9] and fuels for domestic energy use[10]. Indirect pollution coefficients were used for the other expenditure categories, and were calculated by an environmentally extended (EE) input-output (IO) model for 2010.

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[7] In Belgium, company cars are an in-kind benefit provided by the employer. Both commuting-related and private fuel expenses of the employee are often (partly) paid by the employer. Consequently, these expenses do not appear in the survey, hindering comparability with households using their private car for the same ends. As company car users are located in the middle and upper part of the income distribution, leaving this topic unaddressed would result in a distorted estimate of the direct greenhouse gas emissions of these households. We treated this issue by imputing fuel expenses for company car using households based on the observed fuel expenses of the other households. We refer to the Annex for further details.

[8] The Supplementary Material contains more details on the procedure used.

[9] calculated using COPERT, a European road transport emission inventory model.

[10] calculated using publicly available data about the emission content of those fuels. For further details, see (Cooreman et al., 2019, p. 10)

IO analysis is a methodology that uses industry- and product-level data to map supply chains in the economy. The core principle of the methodology is that, over the course of one year, each industry's purchases from itself and from other industries plus their use from inventories (input), equal exactly what was necessary to produce its gross output that year (sales to itself and to other industries plus sales to final consumers plus goods added to inventories). Mathematically, the economy can be expressed by equating total gross outputs ($\boldsymbol{x}$) with intermediate outputs (multiplying the matrix of direct requirements $\mathbf{A}$ with the output vector $\boldsymbol{x}$) plus final demand $\boldsymbol{y}$.

$$\boldsymbol{x} = \mathbf{A}\boldsymbol{x} + \boldsymbol{y} \qquad (1)$$

Using the so-called Leontief inverse $(I - \mathbf{A})^{-1}$ (where I stands for the identity matrix), equation (2) expresses total output $\boldsymbol{x}$ as a function of final demand $\boldsymbol{y}$;

$$\boldsymbol{x} = (I - \mathbf{A})^{-1}\,\boldsymbol{y} \quad (2)$$

When the data are environmentally extended with industry-level air pollution data, it is possible to quantify how much air pollution is embedded in the production process of goods and services. To that end, first a pollution coefficients matrix S has to be constructed. This matrix can be used to transform total output to obtain $\boldsymbol{d}$, which represents total environmental impacts associated with final demand $\boldsymbol{y}$.

$$\boldsymbol{d} = S\,\boldsymbol{x} = S\,(I - A)^{-1}\,\boldsymbol{y} \quad (3)$$

Dividing $\boldsymbol{d}$ by final demand $\boldsymbol{y}$ results in a matrix of indirect pollution coefficients in PEACH2AIR. An element of this matrix, which we denote by e_i^{ind}, expresses the amount of GHG emissions (expressed in grams of CO_2 equivalents – CO_2e) emitted through the supply chain of product *i*, per one euro spent on product *i*. [11]

The pollution coefficients e_i^{ind} are expressed in 2010 basic prices for 354 products, classified in accordance with the Supply and Use Tables (SUT) classification. In order to link them to 2014 HBS expenditures, they were adjusted for inflation (2010 to 2014), for product nomenclature (SUT to COICOP), and from basic prices to purchaser's prices (taking account of excise duties and value added tax).[12]

Eventually, the total HCF of each household, e^{tot}, is given by multiplying their expenditures on each product *i* (exp_i) with the direct (e_i^{dir}) and/or indirect (e_i^{ind}) pollution coefficients of the product and then summing this up for all products:

$$e^{tot} = \sum_{i=1}^{n} exp_i\left(e_i^{ind} + e_i^{dir}\right) \ (4)$$

It is important to note that 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 their homogeneous price, 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).

[11] For the more detailed methodology of IO-based footprint accounting, we refer to Miller and Blair (2012).
[12] For further details, see Frère et al. (2018).

Specifically to our model, we note that the EE-IO model used to construct the PEACH2AIR database is a *single region* EE-IO model. Given that in this paper we only focus on Belgium, this model has the important advantage of producing pollution coefficients at a relatively detailed industry and product level compared to multi-regional models. However, it assumes that the production technology of imported goods is the same as the production technology of the same product produced in Belgium (domestic and foreign S and A are identical in the above equations).

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

2.3. Regression analysis

We analyze determinants of the total household carbon footprint (HCF) in a regression framework. We start with focusing on the main determinant of emissions: living standards, as measured by income and expenditures. These reduced-form models, also called environmental Engel curves (Levinson & O’Brien, 2019; Sager, 2017), are subsequently extended by adding other socio-economic variables to the model.

There is no theoretical model that *a priori* suggests the functional form between income and pollution at the household level (Levinson & O’Brien, 2019). Brännlund and Ghalwash (2008) show that a positive and linear relationship requires very specific assumptions about preferences and the consumption-pollution 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-pollution relationship) fits best the data at hand. Thus, we first test five functional forms that have been used in the literature and assess their performance in fitting the data (Isaksen & Narbel, 2017; Weber & Matthews, 2008) (see Table 1).

A widely used concept in this context is the elasticity of emissions with respect to income or expenditures. It measures the percentage change in emissions associated with a one percent increase in income/expenditures (Wier, Lenzen, Munksgaard, & Smed, 2001). The concept is unit-independent, thus allowing for comparisons across studies on different countries, currencies and time. The concept originates from consumer behaviour theory and has been adopted to HCF research. The formula of the elasticity of GHG emissions with respect to income is

$$\varepsilon = \frac{inc}{e}\frac{\partial e}{\partial inc} \quad (5)$$

where *e* stands for HCF and *inc* stands for income or expenditures.

Table 1. Reduced-form model specifications

Model	Model specification	Elasticity
Linear	$e = \alpha + \beta_1 x + \boldsymbol{\gamma} a + \boldsymbol{\delta} c + u$	$\varepsilon = \frac{x}{e}\beta_1$
Quadratic	$e = \alpha + \beta_1 x + \beta_2 x^2 + \boldsymbol{\gamma} a + \boldsymbol{\delta} c + u$	$\varepsilon = \frac{x}{e}(\beta_1 + 2\beta_2 x)$
Cubic	$e = \alpha + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \boldsymbol{\gamma} a + \boldsymbol{\delta} c + u$	$\varepsilon = \frac{x}{e}(\beta_1 + 2\beta_2 x + 3\beta_3 x^2)$
Level-log	$e = \alpha + \beta_1 \ln(x) + \boldsymbol{\gamma} a + \boldsymbol{\delta} c + u$	$\varepsilon = \frac{x}{e}\frac{\beta_1}{x}$
Log-log	$\ln(e) = \alpha + \beta_1 \ln(x) + \boldsymbol{\gamma} a + \boldsymbol{\delta} c + u$	$\varepsilon = \frac{x}{e}\frac{e}{x}\beta_1 = \beta_1$

As both emissions and expenditures are measured on the household and not the individual level, we also control for household size in the reduced-form models. Similarly to income, there is no *a priori* theoretical model for the functional form about the association between household size and emissions. Household size can be incorporated as a single variable in the regression (see Duarte et al., 2012; Fremstad et al., 2018; Golley & Meng, 2012; Ivanova et al., 2017; Lenzen et al., 2006), thus assuming that household size has a constant partial effect on HCFs. Other authors add dummy variables for each value of household size (Ala-Mantila et al., 2014; Büchs & Schnepf, 2013). We follow the latter approach because it allows for more flexibility, i.e. the effect of an additional household member on emissions can vary at different household sizes. Moreover, we distinguish between adults and children, because the consumption patterns of children are different from those of adults (Gough et al., 2011).

We then extend our model by adding further socio-economic characteristics as explanatory variables. We do not aim to identify causal relationship, 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; Baiocchi et al., 2010; Ivanova et al., 2017).

Our choice of variables to include in the multiple regression models is driven by the existing literature. Our regression model takes the following form:

$$\ln(e_i^{tot}) = \alpha + \beta \ln(inc_i) + \delta_i \boldsymbol{v}_i + \gamma_i \boldsymbol{z}_i + u_i \quad (6)$$

where e_i^{tot} is the total HCF from equation (4) - i.e. the GHG emissions related to yearly consumption of household i and measured in tons of CO_2 equivalents, inc_i the yearly household disposable income of household i, $\boldsymbol{v}_i$ a vector of socioeconomic variables of household i (number of adults, number of children, age of the household head, professional status of the household head, highest educational attainment in the household, region of the household, tenure status), $\boldsymbol{z}_i$ a vector of dwelling-related variables (number of rooms, dwelling type). α, β, δ_i and γ_i are parameter (vectors) to be estimated[13]. We estimate the regression for total emissions and emissions from five consumption categories separately (food, energy and housing, transport, goods, and services; for details about the construction of these categories see Annex).

[13] 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.

We measure HCFs at the household level and not on a per capita basis for two reasons. Firstly, the unit of observation for measuring expenditures in the HBS is the household, and not the individuals therein. Secondly, previous literature suggests that the carbon footprint of children are different from that of adults. Measuring HCFs on a per capita basis "… assumes that all persons make the same 'contribution' to household emissions, that a baby counts the same as an adult" (Gough et al., 2011, p 34). This issue could be solved by applying an equivalence scale that has been developed for income and consumption equivalization. However, there is no evidence for its applicability to emissions. Thus, we use the same unit of analysis as the unit of observation, notably the household.

In the reduced form models we calculate the elasticities of HCFs with respect to both income and expenditures; in the full model specifications, we only include income. This is motivated by the consideration that HCFs are calculated based on expenditures themselves. Nevertheless, we calculate expenditure elasticities in the reduced form models in order to compare our estimates with results from other studies.

In the last step of the empirical analysis, we perform dominance analysis to determine the relative importance of each explanatory variable in explaining the outcome variable, the HCF. This method offers further 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 effect of an incremental change of the explanatory variables on 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 and Budescu (2003) and Luchman (2013, 2015)[14].

3. Results

3.1. Distribution of Belgian HCFs

In this section, we present the distribution of Belgian HCFs according to households' living standards. We measure living standards by the two most commonly used indicators, expenditures and income, which provide a complementary picture. Both concepts may lead to different rankings of households due to differences in assets, saving options and preferences. For example, older (younger) households that finance their expenditures from savings (loans) are ranked higher in the expenditure than in the income distribution. The expenditure concept includes all consumption items that have associated emissions plus three housing-

[14] We use the user-written Stata command 'domin' Luchman (2013, 2015) and use survey weights to calculate parameter estimates in the dominance analysis.

related expenditures which do not have associated emissions (i.e. rent, mortgage payments and imputed rent). Household composition is taken into account by equivalising income and expenditures[15].

There is a positive association between living standards and emissions: households with higher incomes or expenditures have higher emissions (Figure 1). Per capita HCFs grow from 4.6 to 16.5 tons of CO_2e/capita when we move from the lowest to the highest expenditure decile and from 6.1 to 12.4 tons of CO_2e/capita when moving from the lowest to the highest income decile. In line with what could be expected, the association is weaker between emissions and income than between emissions and expenditures. There is even a slight decrease from the 4th to the 6th income decile. The composition of emissions varies across the income and expenditures distribution. Emissions from 'Food' and 'Energy and housing' make up the largest part of emissions in the first decile, while their share decreases when moving up the income ladder. In contrast, emissions from 'Transport', 'Goods', and 'Services' make up almost half of the HCFs at the top of the distribution whereas their share is small at the bottom.

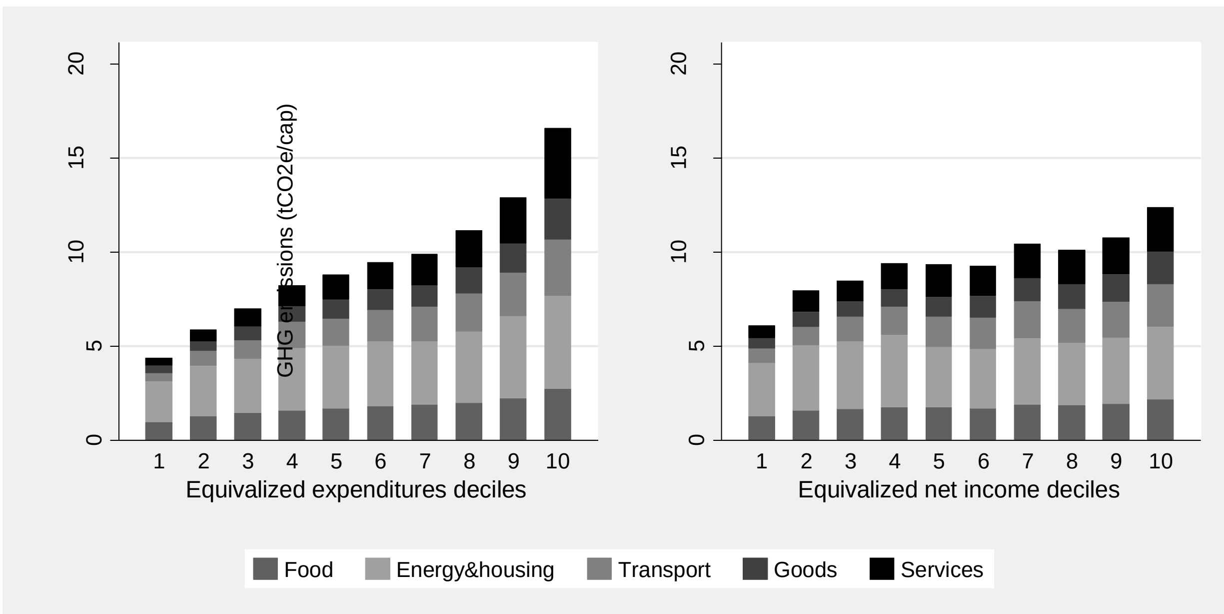

Figure 1. Distribution of Belgian HCFs.

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). We calculate the emission 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/expenditure decile. Emission intensity exhibits a steady decrease from the bottom to the top of both distributions from around 800 to 600 gCO_2e/euro. This is due to the different composition of the consumption bundle at the top and the bottom of the distribution, while the emission intensity of different consumption categories differs greatly. The mean emission intensity of products in the 'Energy and housing' category is more than ten times higher (3809 gCO_2e/euro) than the emission intensity in the 'Goods' category (306 gCO_2e/euro). Given that

[15] We use the widely used modified OECD equivalence scale, which assigns the value of 1 to the household head, 0.5 to each additional adult household member and 0.3 to each child (defined as persons younger than 14).

'Energy and housing' consists of a larger share of the consumption bundle at the bottom of the income/expenditure distribution, emission intensity is lower at the top of the income distribution.

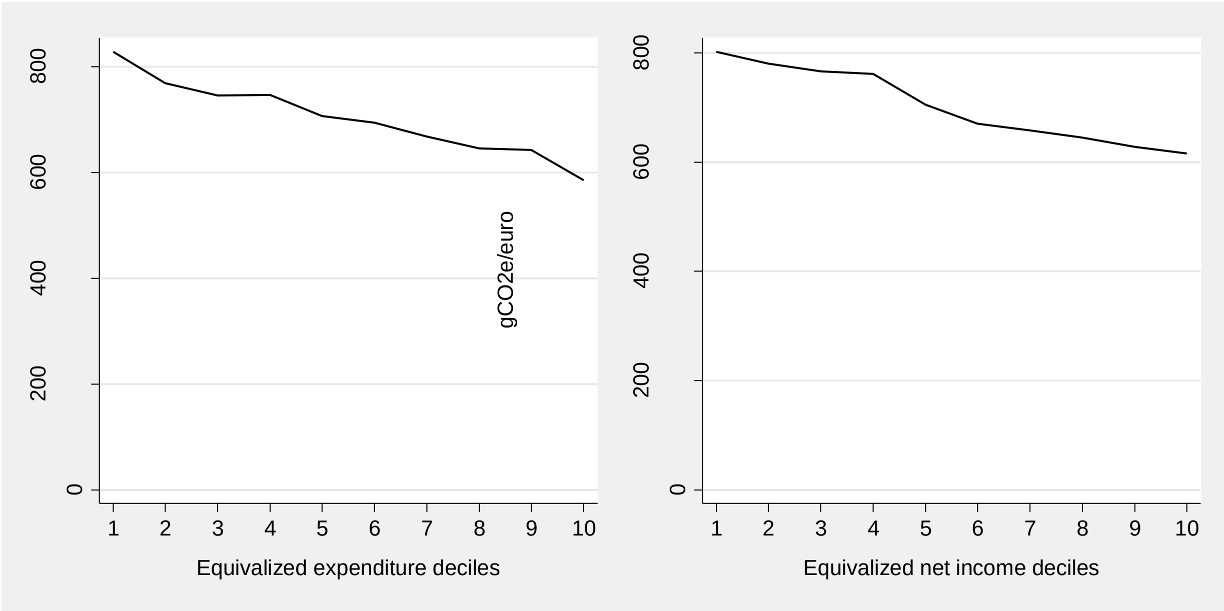

Figure 2. Emission intensity over the expenditure (left) and income (right) distribution

3.2.Elasticity of emissions in a reduced form model

Table 2 lists the elasticity estimates of the HCF with respect to income and expenditures for different specifications of the functional form. Clearly, the functional form of the regression matters quite substantially for the estimated elasticity. The estimated elasticity ranges from 0.6 to 0.8 for expenditures and from 0.27 to 0.48 for income; for all functional forms the elasticity with respect to income is lower than the one with respect to expenditures. Based on the r-squared values we conclude that there is no substantial difference among goodness-of-fit of the different functional form specifications. With the log-log specification we find an elasticity of HCF with respect to income of about 0.47 and with respect to expenditures of about 0.80. We evaluated elasticities both at the mean and at the median of the income and expenditure distributions. The choice does not affect substantially the estimated elasticities.

Table 2. Elasticity estimates in reduced form models

	Linear	Quadratic	Cubic	Level-log	Log-log
Expenditure elasticities					
Evaluated at mean expenditures	0.77	0.80	0.79	0.60	0.80
Evaluated at median expenditures	0.76	0.79	0.79	0.60	0.80
Income elasticities					
Evaluated at mean income	0.29	0.43	0.48	0.39	0.47
Evaluated at median income	0.27	0.41	0.47	0.40	0.47
R-squared					
Expenditures	.67	.67	.67	.62	.66
Income	.37	.39	.40	.39	.37

Notes: (1) We followed the method suggested by Wooldridge (2009: 211-213) to adjust the R-squared calculation in the log-log model in order to be able to compare its value to the other model specifications. (2) Results for the first four model specifications are presented here for households with 2 adults and one child given that elasticities differ according to household type. Results for other household types can be found in the Supplementary Material.

3.3 Regression models and dominance analysis

In this section we present the results of the multiple regression (Table 3) and the dominance analyses (Table 4). 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 0.26 for domestic energy consumption for housing, and is equal to 0.58 for total emissions.[16].

Table 3. Results of multiple regression analyses

	(1) Ln(GHG_total)	(2) ln(GHG_Food)	(3) ln(GHG_Energy_housing)	(4) ln(GHG_Transport)	(5) ln(GHG_Goods)	(6) ln(GHG_Services)
Income	0.323***	0.235***	0.114***	0.589***	0.693***	0.582***
	(0.019)	(0.019)	(0.025)	(0.040)	(0.030)	(0.046)
Number of adults						
1	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
2	0.199***	0.437***	0.103***	0.360***	0.203***	0.175***
	(0.017)	(0.019)	(0.025)	(0.036)	(0.023)	(0.049)
3	0.264***	0.573***	0.149***	0.300***	0.126***	0.236***
	(0.023)	(0.027)	(0.032)	(0.065)	(0.030)	(0.062)
>=4	0.354***	0.738***	0.192***	0.284***	0.140***	0.387***
	(0.029)	(0.026)	(0.043)	(0.056)	(0.032)	(0.086)
Number of children						
0	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
1	0.095***	0.123***	0.070**	-0.038	-0.018	0.269***
	(0.015)	(0.023)	(0.024)	(0.040)	(0.018)	(0.039)
2	0.122***	0.225***	-0.009	-0.088*	-0.066**	0.444***
	(0.015)	(0.022)	(0.025)	(0.039)	(0.020)	(0.050)
3	0.190***	0.316***	0.052	-0.105	-0.084*	0.636***
	(0.034)	(0.032)	(0.054)	(0.075)	(0.033)	(0.087)
>=4	0.292***	0.428***	0.122	0.093	0.051	0.730***
	(0.055)	(0.069)	(0.118)	(0.151)	(0.053)	(0.185)
Age of reference person	0.005***	0.010***	0.005***	-0.001	0.001	0.008***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Prof.stat.refpers.						
working	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
unemployed	-0.085**	-0.084	0.018	-0.404***	-0.198***	-0.246***
	(0.030)	(0.045)	(0.048)	(0.072)	(0.040)	(0.069)
student	-0.067	-0.120	-0.034	-0.360**	-0.104	0.090
	(0.098)	(0.096)	(0.187)	(0.136)	(0.115)	(0.178)
homemaker	-0.046	-0.127*	0.051	-0.235	-0.096	-0.199
	(0.064)	(0.061)	(0.133)	(0.204)	(0.061)	(0.179)
incapacitated	-0.046	0.009	0.047	-0.406***	-0.067	-0.062
	(0.034)	(0.037)	(0.059)	(0.074)	(0.039)	(0.075)
pension	-0.049*	-0.030	-0.007	-0.149**	0.003	-0.053
	(0.025)	(0.024)	(0.037)	(0.056)	(0.033)	(0.060)
Education						
primary or less	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
lower secondary	0.025	-0.023	0.060	0.055	0.017	0.083
	(0.031)	(0.044)	(0.065)	(0.091)	(0.045)	(0.074)

[16] We tested for the presence of multicollinearity by calculating variance inflation factors (VIF). The VIF values were always below 10, which suggests that there is no evidence for multicollinearity (Wooldridge, 2009, p. 99).

	(1) Ln(GHG_total)	(2) ln(GHG_ Food)	(3) ln(GHG_Energy _housing)	(4) ln(GHG_Tra nsport)	(5) ln(GHG_Good s)	(6) ln(GHG_Services)
upper secondary	0.092**	0.044	0.074	0.262**	0.110**	0.301***
	(0.030)	(0.040)	(0.051)	(0.081)	(0.040)	(0.077)
tertiary	0.173***	0.147***	0.092	0.323***	0.236***	0.515***
	(0.032)	(0.040)	(0.055)	(0.077)	(0.040)	(0.078)
Region						
BXL	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
VL	0.019	-0.034	-0.021	0.170*	0.035	0.080
	(0.028)	(0.025)	(0.038)	(0.073)	(0.022)	(0.061)
WA	0.100***	-0.016	0.200***	0.314***	0.017	-0.108
	(0.029)	(0.024)	(0.038)	(0.075)	(0.023)	(0.063)
Tenure status						
Owner	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Tenant	-0.109***	-0.050*	-0.060*	-0.242***	-0.113***	-0.315***
	(0.016)	(0.024)	(0.026)	(0.045)	(0.018)	(0.043)
Number of rooms						
1	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
2	0.185***	0.168*	0.119	0.184	0.126	0.348***
	(0.052)	(0.065)	(0.084)	(0.156)	(0.066)	(0.091)
3	0.248***	0.095	0.218*	0.342*	0.177*	0.462***
	(0.049)	(0.064)	(0.087)	(0.154)	(0.071)	(0.092)
4	0.323***	0.139*	0.330***	0.473**	0.186**	0.465***
	(0.047)	(0.068)	(0.083)	(0.153)	(0.071)	(0.092)
5	0.356***	0.196**	0.405***	0.473**	0.203**	0.466***
	(0.048)	(0.069)	(0.088)	(0.158)	(0.071)	(0.092)
>=6	0.398***	0.230***	0.471***	0.429**	0.236***	0.516***
	(0.049)	(0.067)	(0.088)	(0.165)	(0.069)	(0.097)
House type						
Detached	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Semi-detached	-0.083***	-0.008	-0.134***	-0.175***	-0.012	-0.010
	(0.012)	(0.016)	(0.021)	(0.030)	(0.020)	(0.030)
Apartment	-0.162***	-0.061*	-0.371***	-0.254***	-0.066*	0.137**
	(0.019)	(0.025)	(0.035)	(0.050)	(0.028)	(0.052)
Other	-0.015	-0.046	-0.118	-0.155	0.156	0.170
	(0.082)	(0.135)	(0.171)	(0.188)	(0.126)	(0.191)
Constant	-1.342***	-2.389***	-0.171	-6.080***	-7.021***	-6.931***
	(0.218)	(0.221)	(0.298)	(0.470)	(0.295)	(0.483)
Observations	6124	6124	6124	6124	6124	6124
R^2	0.581	0.486	0.265	0.411	0.620	0.354

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Income is the most important determinant of the total HCF, accounting for 28 percent of the explained variance in total HCF (see Table 4). The coefficient of the income variable is 0.32, i.e. a one percent increase in household income is associated with a 0.32 percent increase in household GHG emissions, holding other factors constant (see Table 3). This elasticity is lower than in the reduced-form log-log model, indicating that part of the bivariate association of emissions and income runs through other factors that are associated with income. Both the importance of income in the dominance analysis and the income elasticity of the HCFs vary greatly across the five categories. While income is the most important variable in the 'Goods' and 'Services' models, accounting for 43.3 and 32.2 percent of the explained variance, respectively, its importance is much less in the 'Food' and 'Energy and housing' models. Income elasticities of emissions in the ‘Energy and housing’ and ‘Food’ models are also lower than in the other models, being 0.11 and 0.24 percent, respectively, ceteris paribus. These two categories mainly incorporate goods and services that satisfy basic needs. As a result, it can be expected that low income households spend a proportionally higher share of their income on these categories, and high-income households spend a relatively lower proportion of their income (even when in nominal terms, they spend much more). Consequently, demand and subsequent emissions from these consumption categories vary less by overall income levels. In contrast, the emissions from the other three product categories are more income-elastic, as reflected by the higher elasticities for ‘Transport’(0.59), ‘Goods’ (0.69), and ‘Services’ (0.58). Richer households spend higher shares of their overall expenditures on these three categories (cf. Figure 1).

Household size has a positive effect on the HCF in all models and it is even the most important variable in the ‘Food’ model (see Table 4). The size of the estimated coefficients of the household size dummies varies across the models (Table 3). In the ‘Total’ model, a household with two (three) persons emit 20 (26) percent more than a single-person household. The emissions of bigger households are higher than those of smaller households, but emissions vary far from proportionally with household size. This implies that on a per capita basis, emissions fall with growing household size, and quite considerably so in the case of the total HCF. The effect of household size differs greatly according to consumption category. The estimated coefficients for the adult and child variables are smallest in the ‘Energy and housing’ model. An additional household member adds little to heating and other housing-related expenses and subsequent emissions, i.e. the economies of scale effect is strongest in case of energy and housing related HCFs. The coefficients for the adult and children variables are highest in the ‘Food’ model, reflecting that the economies of scale effect is weakest in case of food and drinks related HCFs. The adult dummies have much higher estimated coefficients and are more important in the dominance analysis than the child dummies in all models (except ‘Services’). This reflects that children consume less resources than adults, and hence add far less to overall household emission levels than adults. The category-specific regression results show that the positive effect of children in the ‘Total’ model comes mainly from emissions from ‘Food’ and ‘Services’. The estimated coefficients of children in the ‘Energy and housing’, ‘Goods’, and ‘Transport’ regressions are small (in some cases even negative) and insignificant.

The two variables related to **characteristics of the dwelling** (number of rooms and type of house) 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 the ‘Energy and housing’ specification, where the housing-related variables have the most important explanatory power (close to 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 13 and 37 percent lower than those of households living in detached houses, ceteris paribus. In Belgium, 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’ probably reflect longer commuting and other travel distances for households that live away from urban centers.

Age (i.e. age of the reference person) has a small and significant positive effect on total emissions (Table 3). This might reflect the fact that values and lifestyles change with age, which translates into different consumption and emission patterns (see also Büchs & Schnepf (2013; Golley & Meng (2012). Note however that age is among the least important variables in all models.

The **professional status** variable refers to the household head, with ‘working’ as reference category. The estimated coefficients of the other categories are negative in almost all models, i.e., households where the household head is unemployed, student, incapacitated, homemaker or in pension emit less compared to households where the head is working. Only in the ‘Energy and housing’ model are the estimated coefficients of professional status categories positive. A plausible explanation for this can be that non-working people spend more time at home, which translates into higher heating requirements, and thus higher emissions in the ‘Energy and housing’ consumption category. Based on the dominance analysis, the importance of professional status is the highest in the ‘Transport’ model. Emission from transport are 41 (40) percent less for households with an incapacitated (unemployed) household head, than for households with a working household head. This finding is likely to reflect that unemployed and incapacitated people commute less to work and/or use less emission intensive mobility means (e.g. public transport). Moreover, the fiscally attractive system of “salary cars”, where a car is provided to employees as a way of (social contributions exempt) remuneration which leads relatively many employees to use the car for daily commutes.

The higher the **educational attainment** in the household, the higher the household’s emissions. Compared to the reference category (‘primary or less’), households with an upper secondary or a tertiary education level emit significantly more. We find the strongest association between education and emissions in the regression results for ‘Services’, where a household with tertiary education is associated with 52 percent higher emissions as compared to the reference category. This may be driven by the fact that people with higher educational attainment have different preferences, norms and values related to how to spend their free time, translating into more emission-intensive consumption patterns, than people with lower educational attainment. However, our model cannot capture the exact driving forces behind the positive education-emissions relationship. This certainly is an area for further research.

For the geographical dimension, we can only look at differences according to NUTS1 **region** variable. Belgium has three regions: Brussels-Capital Region (reference category), Wallonia and Flanders. Households in Wallonia emit more than households in Brussels and Flanders. Households in Wallonia emit 10 percent more than those in Brussels, which is mainly driven by emissions from ‘Energy and housing’ and ‘Transport’. This relates to the fact that houses in Wallonia are older and that the pollution-intensive types of heating, coal, fuel oil and wood, are more prevalent. In addition, travel, commuting, and driving distances are longer in Wallonia than in Brussels (Verhetsel et al., 2009), which is reflected in a large and significant effect in the ‘Transport’ regression. We do not have data on driving distances, urban/rural distinction, or the quality and density of the public transport system. Ideally, we would include these variables in the transport regression. We assume that the region variable picks up the effects of these factors.

Occupancy is a dummy variable, that distinguishes between owners and tenants. We find that the HCFs of tenants is less that the HCFs of owners. The difference is the biggest in the ‘Transport’ and ‘Services’ models, where tenants emit respectively 24 and 32 percent less than owners, ceteris paribus.

Table 4. Results of dominance analysis.

	Total	Food	Energy and housing	Transport	Goods	Services
income	28.3	24.4	10.1	29.2	43.3	32.2
adults	19.8	35.4	10.8	17.0	16.5	14.0
children	3.9	5.0	1.4	1.8	1.8	8.3
age	1.2	4.0	3.5	0.8	0.4	1.0
profstat	5.6	4.8	2.5	11.3	8.7	7.6
educ	6.3	4.8	1.7	7.8	9.6	12.7
region	2.0	0.5	12.1	3.0	0.9	2.8
roomnr	14.6	10.8	22.9	11.1	8.2	9.0
house_type	10.1	5.7	26.1	9.1	4.4	3.1
occupancy	8.2	4.6	9.0	8.9	6.1	9.1

Note: Numbers indicate the percentage contribution of each variable to the overall fit measure (R-squared) in the regressions presented in table 3.

4. International comparison and discussion

The distribution of household GHG emissions we find for Belgium follows a similar pattern as the one in Christis et al. (2019), who look at Flanders (the largest region in Belgium in terms of population size) in a bivariate framework, but also as those found in other countries at similar development level, such as the UK (Büchs & Schnepf, 2013; Gough et al., 2011), Netherlands (Isaksen & Narbel, 2017), Spain (Duarte, Mainar, & Sánchez-Chóliz, 2010; Duarte et al., 2012), Australia (Lenzen et al., 2006), and the US (Weber & Matthews, 2008). The composition of emissions change along the income distribution. Emissions from Energy and Housing and Food consist of a larger part of total emissions at the bottom of the income distribution, emissions from Transport and Services is relatively more important at the top.

We found that the emission intensity of consumption bundles decrease 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 have been found in the Netherlands, the UK and China (Golley & Meng, 2012; Kerkhof, Benders, & Moll, 2009). In these countries, households at the bottom of the income distribution spend higher share of their total expenditures on emission-intensive products, especially housing energy. This negative relationship is, however, not a necessity, as is shown by the cases of Norway, Sweden and Denmark, where emission intensity either increases or stays constant with growing income levels. In the case of Sweden, the driving force behind the positive emission intensity-income relationship is likely to be the fact that the share of domestic energy emissions does not vary considerably with income, as low-income households use low-emission intensive district heating in apartment buildings, while high-income households live in detached houses with no access to district heating (Kerkhof, Benders, et al., 2009). For Denmark, Wier et al. (2001) find that direct CO_2 emission intensity falls, while indirect CO_2 intensity does not decrease with increasing income levels. 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[17]. These outcomes show that the

[17] Lenzen et al. (2006) found the same pattern and explanations for energy requirements in Brazil.

emission intensity of the national energy supply is a key determinant of the income-energy intensity relationship.

The elasticity of emissions with respect to income and expenditure that we find for Belgium are in line with elasticities estimated for other countries (see Table 3). We find elasticities above zero but lower than one, which means that there is a relative, but no absolute decoupling between income and emissions (in the cross-section). The studies that present elasticities both in terms of income and expenditures, also find that the elasticity of emissions with respect to income is lower than the one with respect to expenditures Partially, this is probably attributable to the fact that HCFs are estimated as a function of consumption expenditures (see also Ala-Mantila et al., 2014; Weber & Matthews, 2008)[18].

Table 5. Income and expenditure elasticity of GHG/CO_2 emissions in the literature

Paper	Country	Income elasticity	Expenditure elasticity
Ala-Mantila et al. (2014)	FI	0.607_{g} ($0.577_{g,o}$)	0.802_{g} ($0.790_{g,o}$)
Büchs & Schnepf (2013)	UK	$0.432_{c,o}$	
Duarte et al. (2012)	ES		$0.84_{c,o}$
Fremstad et al. (2018)	US		$0.728_{c,o}$
Girod & Haan, (2010)	CH		0.94_{c} (1.06_{c}^{1})
Isaksen & Narbel (2017)	NO		0.99_{c}
Kerkhof et al. (2009)	NL		0.84_{g}
Lenzen (1998)	AU	0.55_{g}	0.70_{g}
Levinson & O'Brien (2019)	US	0.393	
Steen-Olsen et al. (2016)	NO		1.14_{g}
Weber & Matthews (2008)	US	$0.35\text{-}0.52_{g,o}$	$0.6\text{-}0.7_{g,o}$
Wier et al. (2001)	DK	0.55_{c}	0.70_{c}
This paper	*BE*	*$0.22\text{-}0.56_{g,o}$*	*$0.76\text{-}0.95_{g,o}$*

Note: c: CO_2. g: GHG. o: other controls included in the regression (other than income/expenditures). 1: Without correction for scale economies

The number of studies that present elasticities for different consumption categories is limited and comparability across studies should be treated with caution (see Table 5 and 6). The only study that is directly comparable with ours is the one from Büchs and Schnepf (2013). For the UK, they find an income elasticity of total consumption of 0.43, which is somewhat higher than our 0.32 estimate. Their elasticities of emissions from 'Energy and housing' and 'Transport' with respect to income are 0.19 and 0.59, respectively, which is close to our respective estimates of 0.11 and 0.59. The other studies use expenditures[19] instead of income in their regressions. Moreover, except for Ala-Mantila et al. (2014), they do not include other explanatory variables (Girod & de Haan, 2010; Isaksen & Narbel, 2017; Steen-Olsen et al., 2016). Despite the caveats with respect to comparability, a general pattern emerges from these studies: expenditure/income elasticities of emissions related to consumption categories that satisfy basic needs, such as heating and food, are much lower than those of more luxurious product groups, such as recreation and transport.

[18] Our expenditure variable captures savings only insofar they are spent on mortgages.
[19] Note that the grouping of expenditure categories is not the same across studies.

Table 6 . Consumption category specific elasticity estimates in the literature

Paper	Country	Food	Energy, housing	Transport	Goods	Services
Ala-Mantila et al. (2014) $_{g,e}$	FI	0.512	0.133		1.233	1.420
Büchs & Schnepf (2013) $_{c,i}$	UK		0.187	0.598		
Girod & Haan, (2010) $_{g,e}$	CH	0.08[1]	0.53	1.21	1.30	0.54[2], 1.26[3]
Isaksen & Narbel (2017)$_{c,e}$	NO	0.50	0.25[4]	1.01		
Steen-Olsen et al. (2016) $_{g,e}$	NO	0.98	1.02	1.48	1.26-1.29	0.57-1.05
This paper	*BE*	*0.235*	*0.114*	*0.589*	*0.693*	*0.582*

Note: c: CO2. g: GHG. e: expenditure elasticity. i: income elasticity. 1: beverages are excluded from the 'food' consumption category. The elasticity of beverages is 0.73. 2: time-using services (e.g. hair-dresser). 3: non-time-using services. 4: Only energy, not housing. Expenditure elasticity of emissions categories 'clothing' and 'other' are 1.3 and 1.16, respectively.

Using dominance analysis, it was confirmed that in Belgium income and household size contribute most to the explanatory power of the models. Yet, the importance of housing-related variables is sizable, as well as the contribution of education in the explanatory power of the regression modelling the emissions from services. 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), 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 when living together, in terms of the level of GHG emissions[20].

We found that educational attainment has a small effect on total HCFs, while its importance is stronger in the 'Services' model. This finding is in line with the literature, where mixed results were found: Büchs & Schnepf (2013) and Poom & Ahas (2016) find that educational attainment and emissions are positively associated even after controlling for other factors, while Lenzen et al. (2006) found a negative association between education and energy requirements in Australia and Japan (and a positive one in Brazil, Denmark and India). Ivanova et al. (2017) also find a positive association between education and HCFs, though their analysis is not at the micro level of the household, but at the regional level[21]. Education can be seen as a proxy for differences in lifestyle, preferences and attitudes, which play a role in other channels as well, for instance in the interplay between housing, transport and region. These preferences and attitudes impact on the choice of the location and the type of dwelling, with impacts on daily travel distances, and home energy requirements[22].

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 CO_2-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

[20] Note that sharing does not only occur within households, but also between households because of urbanity and spatial proximity. Fremstad et al. (2018, p. 143), e.g. finds for the US that "increasing urban density has the potential to offset the upward pressure placed on per capita emissions by declining household size." As we have no information about urbanity, we are not able to investigate the interaction with household size.

[21] For a more elaborate discussion of the relation between emissions and education, see for instance Zhang et al. (2015, p. 878).

[22] There are other, more systemic, driving factors of the relation between housing, transport and related emissions: spatial configuration, degree of urbanity, population density, geography, job density, public transport's quality, availability, and coverage. Deeper analysis of these factors are out of the scope of this paper, however, we refer to some studies that addressed these issues in the Belgian context (Boussauw, Neutens, & Witlox, 2010; Boussauw & Vanoutrive, 2017; Dujardin, Pirart, Brévers, Marique, & Teller, 2012).

(consumption categories that rise with income in their relative importance in the consumption basket) or housing, energy & food (which decrease in relative importance over the income distribution). 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 influence of socio-economic characteristics go beyond merely income: several socio-economic factors are associated with emissions within specific consumption categories. This may help to identify target groups of special interest for policies that aim to discourage high-emission types of consumption. Third, the statistical trend towards smaller households that we observe in demographic statistics puts an upward pressure on emissions (Bradbury et al., 2014), given the relatively strong economies of scale that 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 to be made from household economies of scale. Fourth, apart from the factors mentioned above, the results also point to the interaction of HCFs with infrastructural configurations, and spatial planning (as illustrated by the importance of the regional dimension in our results). Thus, it is important to stress the country- or region-specificity of our results. The relative importance of the different consumption categories in total emissions as well as the resulting distributional patterns, follow to an important extent from the pathway taken by national infrastructures: the spatial and transport organization, the CO_2-intensity of the 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 by households, while taking into account potential adverse distributive effects. This applies in particular to consumption of domestic energy and transport, where households may have somewhat more room for maneuver compared to emissions associated with the consumption of goods and services. Although we are convinced that demand-side measures have a role to play to achieve strong reductions in GHG emissions in a relatively short timeframe, it should be clear that consumption by households operates within a broader context on which individual households have a much lower 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. Combining the HBS with an EE-IO model, our dataset contains socio-economic variables, housing information, and detailed expenditures with associated environmental impact, at the household level. Our study is the first multivariate EE-IO analysis for Belgium.

Using regression analysis we find that income, household size, age, education and the size of the house have significant positive effects on household GHG emissions. Unemployment, living in an apartment (rather than living in a house), and being a tenant are associated negatively with household emissions.

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 not in proportion to their relative income position (in the cross-section, an increase in income of 10% is associated with a 3.2% rise in emissions) and (b) households with more members emit more in absolute terms, but less on the 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 and housing). It is the least sensitive to changes in household size: emissions from heating do not increase significantly with an additional household member.[23] This same consumption category is also found to be – along with food fulfilling basic needs – most income-inelastic, contributing to the relatively low overall income elasticity of emissions.

Finally, while our analysis offers a good starting point for understanding GHG emissions by households in Belgium, obviously, for designing policies more specific analyses are required. 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 pollution coefficients either by increasing their level of disaggregation such that it would be possible to look in more detail into specific consumption categories, or by combining the level of detail of 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 in these dynamics is a crucial complement to deepen our understanding of how consumption patterns can evolve to more sustainable outcomes.

[23] Conversely, emissions from food consumption grow nearly proportionally when household size increases.

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Annex

Table A1. Descriptive statistics of continuous variables

Variable	Description	Mean	Std.err.	Min	Max
GHG_Total	Total household GHG emissions	19.0	0.3	0.0	182.7
GHG_Food	Household GHG emissions from food consumption	3.6	0.0	0.0	18.4
GHG_Energy_housing	Household GHG emissions from energy and housing related consumption	6.4	0.1	0.0	74.1
GHG_Transport	Household GHG emissions from transport	3.3	0.1	0.0	21.4
GHG_Goods	Household GHG emissions from consumption of goods	2.4	0.0	0.3	34.8
GHG_Services	Household GHG emissions from consumption of services	3.3	0.1	0.0	157.7
Income	Net disposable household income	37414.7	510.3	0.0	514080.0
Expenditures	Household consumption expenditures. Rent, imputed rent, and mortgage payments are not included	28350.5	402.9	2664.5	176680.9
Age	Age of reference person in the household	51.4	0.3	16.6	93.9

Notes: GHG emissions are measured in tons of CO_2 equivalents. Tabulations of categorical variables are listed in the supplementary material.

To make interpretation easier, we aggregated the 1092 6-digit COICOP categories into 5 big categories: Food and drinks, Energy and housing, Transport, Goods, Services. The table below summarizes this aggregation (some aggregate codes were subdivided into 'goods' and 'services'):

Table A2. Aggregation of COICOP categories.

1-digit COICOP category	Aggregate category
01 Food and non-alcoholic beverages	'Food and drinks'
02 Alcoholic beverages, tobacco	'Food and drinks'
03 Clothing and footwear	'Goods'
04 Housing, water, electricity, gas and other fuels	'Energy and housing'
05 Furnishings, household equipment and routine maintenance of the house	'Goods' or 'Services'*
06 Health	'Goods' or 'Services'*
07 Transport	'Transport'
08 Communication	'Goods' or 'Services'*
09 Recreation and culture	'Goods' or 'Services'*
10 Education	'Services'
11 Restaurants and hotels	'Services'
12 Miscellaneous goods and services	'Goods' or 'Services'*

* Subclasses of the 1-digit COICOP category include both goods and services. In order to distinguish them, we use a variable which categorizes the 3-digit COICOP nomenclature into durable goods, semi-durable goods, non-durable goods, and services. This variable was downloaded from the website of the Statistical Division of the United Natio