Carbon Inequality in the EU

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Abstract

Pricing greenhouse gas emissions is a crucial tool in environmental policy, following the Pigouvian principle. However, carbon pricing can have significant distributional consequences. To address these concerns, we examine household-level inequality in greenhouse gas emissions across the entire EU. We develop a unique cross-sectional dataset of household carbon footprints in all 27 EU countries by merging data from EXIOBASE, a multi-regional, environmentally extended supply-use dataset, with the European Household Budget Survey.

Our findings reveal substantial inequality in greenhouse gas emissions both between and within countries, with the major variation occurring within countries. Interestingly, net income is a weak predictor of carbon footprints, both across and within countries.

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1 Introduction

Pricing greenhouse gas emissions is an essential tool in environmental policy. While following the Pigouvian principle, pricing instruments can also have significant distributional consequences. The distributional effects of carbon pricing are a major concern in the political economy of environmental regulation and they pose a substantial threat to the implementation of pricing instruments. In the EU, where the European Emissions Trading System (ETS) is already in effect, carbon pricing presents both across-country and within-country distributional challenges. These issues create multidimensional political and economic pressure on extending the ETS to additional sectors, such as housing and transportation.

In this paper, we analyze the distribution of household-level carbon footprints across the 27 states of the European Union. To achieve this, we develop a unique and detailed micro dataset of household greenhouse gas (GHG) emissions.[1] We define household greenhouse gas emissions as the amount of indirect and direct emissions related to the consumption of goods and services of private households. This approach is not without controversy. In the domain of private consumption, applying the polluter pays principle is somewhat challenging. It is evident that households are not directly responsible for the emission of greenhouse gases that emerge during the production process of consumption goods; the immediate responsibility lies with the producers. However, as economists, we are interested in how carbon prices may impact different households. Our measure of the *household carbon footprint* or *household greenhouse gas emissions*, terms we use synonymously, provides insights into these redistributional concerns. To measure household-level GHG emissions, we integrate data from the EXIOBASE project, a multi-regional, environmentally extended supply-use dataset, with detailed consumption data from the European Household Budget Survey. This comprehensive dataset enables us to explore the dimensions of both between- and within-country inequality in household carbon footprints within the EU.

Our primary data source for GHG emissions is the EXIOBASE dataset. The EXIOBASE project encompasses 49 regions, including 44 countries – 27 EU member states and 17 other major countries – as well as five "Rest of the World" (RoW) regions. The foundation of EXIOBASE is a comprehensive input-output framework that traces the production processes of 200 different product groups throughout their entire supply chains, from origin to destination. Beyond the economic data typically used to construct input-output tables, the EXIOBASE dataset includes crucial environmental extensions, most notably an emissions account that records data on emissions to air for 27 different pollutants, both from combustion and non-combustion sources. These emissions are allocated through the supply chains of the product groups to their final consumption purposes. Consequently, we can determine the direct and indirect emissions associated with the consumption of

[1] In addition to carbon dioxide, total greenhouse gas emissions typically include methane, nitrous oxide, and various fluorine compounds. These emissions are often measured in CO2-equivalents.

200 different product groups across all EU countries.

On the household side, we utilize the 2015 Household Budget Survey (HBS) of the European Union. The HBS comprises a series of national consumption expenditure surveys conducted by EU member states and several other European countries. Its primary focus is on households' private consumption expenditure on goods and services. Additionally, the survey includes information about the households and their members, such as demographics, income, and other socio-economic characteristics. Participating households are asked to record their expenditures over a specified period. The consumption expenditure data is then categorized based on the 5-Digit COICOP classification.[2]

A key challenge in our data work is matching the aggregate greenhouse gas emissions data by product category from the EXIOBASE project with individual-level consumption expenditure data from the HBS. This process involves translating the 200 product categories in the environmentally augmented input-output tables into the consumption categories used in the COICOP classification. For some goods and services, this translation is straightforward, such as for rice, milk, eggs, financial services, and educational services. However, for other products, it is more complex; for example, "Gas/Diesel Oil" is used both for driving cars and heating homes. Once each product group is matched to its corresponding consumption purposes, we calculate the total greenhouse gas emissions associated with each consumption category for each country. Finally, we allocate these GHG emissions to different households in each country based on their expenditure on each consumption purpose. This approach results in a micro dataset that includes consumption expenditure on various goods and services along with the corresponding household-level greenhouse gas footprint. From this, we calculate the total carbon footprint of each household.

We derive a series of stylized facts on household-level greenhouse gas emissions. Our findings indicate that the majority of consumption-related emissions are indirect, emerging somewhere along the supply chain. Direct emissions – those directly associated with the consumption process of households – play only a minor role. This is in line with the result of Duarte et al. (2021). On average, a household's carbon footprint amounts to approximately 17.5 tons of greenhouse gas emissions per year, measured in CO2-equivalents. The bulk of these emissions are related to the consumption of food, housing (including energy), and transportation. Across EU countries, there is significant heterogeneity in household-level GHG emissions. For instance, households in countries like Romania, Croatia, Hungary, and Bulgaria have footprints of around 10 tons per year, whereas this number exceeds 30 tons in Greece, Cyprus, and Luxembourg. Major cross-country variation in greenhouse gas footprints predominantly arises from differences in emissions related to housing energy and transportation.

Within-country variation in households' carbon footprints is an order of magnitude greater than cross-country variation. A formal decomposition using general-

[2]The European Standard Classification of Individual Consumption by Purpose.

ized entropy indices reveals that around 85 percent of the EU-wide inequality in households' total carbon footprints stems from within-country inequality, while only 15 percent is due to cross-country inequality. However, this is not true for all components of household-level GHG emissions. For instance, when considering housing energy alone, almost 40 percent of the EU-wide inequality in GHG emissions arises from cross-country variation. For transportation, this figure is 25 percent. These results highlight the significant role of geography in shaping a country's GHG emissions.

Carbon footprints are particular in that, unlike for income and consumption, a high average level of household GHG emissions in a country tends to be associated with low inequality, and vice versa. More generally, income is only a weak predictor of carbon emissions. This is true in a cross-country setting, where average price-level adjusted net income explains only 36 percent of the cross-country variation in average GHG emissions. Additionally, net income inequality and inequality in household carbon footprints only correlate weakly. The same is true for consumption, suggesting that in the cross-section of countries, the composition of the consumption basket as well as the emission intensities associated with certain consumption components are the main drivers of the variation in household greenhouse gas emissions.

The weak relationship between household net income and GHG emissions also holds in the cross-section of households within a given country. One central issue related to this finding is the consumption-income relationship, which is highly nonlinear. Households at the bottom of the net income distribution often consume more than their instantaneous income, while those at the top save a substantial part of their available budget. As instantaneous net income is obviously not a great predictor of consumption, it is not surprising that it doesn't explain much of the variation in carbon inequality across households.

Within countries, the relationship between total household consumption and total household GHG emissions is much tighter. Household-level consumption can explain around 63 percent of the variation in carbon footprints. Yet, after accounting for the effects of consumption, another 37 percent of the total variation in emissions across households remains unexplained. This variation arises from both systematic variation of household consumption baskets along the income distribution and unsystematic variation of consumption behavior for a given income or consumption level. Systematic variation comes from the fact that poorer households have relatively higher consumption of food, real estate, and housing energy. While these households consume less transportation and other goods and services, they still exhibit a somewhat higher emissions intensity per euro spent. Unsystematic inequality around the consumption profile of households is still large, with a coefficient of variation around 0.25 to 0.30 for most consumption levels.

Our results have important implications for the design of models of the household carbon footprint. Models of the cross-section of countries must address the emissions intensities of different consumption components as well as varying con-

sumption baskets across countries. For researchers focused on within-country inequality, a primary task is to develop a suitable model of the income-consumption relationship. By providing an appropriate model of the determinants of consumption, one can explain approximately 63 percent of household carbon footprints. This suggests that static models, where net income and consumption typically coincide, are not very effective in delivering accurate outcomes.

Regarding carbon pricing, an important implication of our findings relates to the extent to which carbon pricing is implemented in a country. The importance of emissions related to certain consumption components varies along the income distribution. Households with lower net earnings tend to generate more emissions from food and housing energy, while for wealthier households, transportation and the consumption of other goods and services play a more significant role. If all carbon emissions are priced universally, GHG emissions intensities per euro spent do not vary much between poor and rich households. However, the implications of carbon pricing would look quite different if only certain types of carbon emissions (e.g., those related to food and household energy) were subject to carbon pricing.

Our paper is organized as follows. After a brief review of the literature, Section 2 describes the data sets used and the matching procedure between aggregate emissions data and household-level consumption data. In Section 3, we provide a set of stylized facts of cross-country and within-country inequality of carbon footprints. Section 4 provides a formal decomposition of the between- and within-country carbon inequality, and Section 5 discusses the relationship between household income and carbon emissions. Section 6 offers some concluding remarks.

Literature review to be added

2 A micro database of household carbon emissions

2.1 The EXIOBASE environmentally extended supply-use tables

The first important source of date we use is the EXIOBASE dataset, which consists of environmentally extended multi-regional supply-use/input-output tables, see Stadler et al. (2018). We use version 3 of the monetary EXIOBASE dataset, which originally contained time series data from 1995 to 2011 and was later extended up to the year 2022[3]. It covers 49 different regions consisting of 44 countries, including the 27 EU member states and 17 larger countries, as well as five ¨Rest of the World¨ (RoW) regions. Table A.1 contains an overview of those regions. Two different databases are provided for each year, a product by product and an industry by industry database. We concentrate on the product by product

[3]At this point, it should be emphasized that the original data series ends in 2011. The extension of the data set to 2022 was based on estimates using auxiliary data, predominantly trade and macroeconomic data. For more information see Stadler et al. (2021).

dataset, which contains 200 different product classifications based on the technological assumptions of the industry. Among them are a number of different food products, various fuels used for space heating, products used to generate electricity as well as multiple transportation services. The included product categories are displayed in Table E.11 and more information about the dataset is available at Stadler et al. (2018).

The foundation of EXIOBASE is a basic input-output framework, see Leontief (1936) and Leontief (1970). Let the vector x contain the gross output (in M.EUR) of each product in each of the 49 regions covered by EXIOBASE. Now let the matrix A denote the direct requirement (or technical coefficients) matrix. Using this matrix, we can calculate all national and international intermediate product flows as Ax. Now when we let matrix Y denote final demand for each good in each region,[4] the requirement that every produced good has to be put to use either as intermediate input or final consumption good leads us to the market balance equation

$$x = Ax + Y \quad \Rightarrow \quad x = (I - A)^{-1}Y =: LY,$$

where I is the identity matrix. The matrix L is called the ¨Leontief inverse matrix¨ and shows the relation between the production of goods and final demand. A more detailed overview of the calculations and the input-output analysis in general can be found in Miller and Blair (2009).

In addition to the data usually needed to construct input-output tables, the EXIOBASE dataset provides some environmental extensions. The energy account includes supply and use data of around 60 energy products based on the extended energy balances of the International Energy Agency (IEA). The emission account provides data of emissions to air for 27 different pollutants, both for combustion and for non-combustion emissions. The water, material, land and labor accounts provide additional extension data such as the water use or socioeconomic factors associated with the respective product types. More information on the different accounts can be found elsewhere (Stadler et al. (2018)). These impact factors of or involved resources in the production of certain products make up the so called stressor data. The EXIOBASE dataset provides this data in the form of two different sets of extensions. While the economic data of the MRIO tables is given in million Euro (M.EUR), the extension data in those two accounts is expressed in the unit of the respective stressor. Uncharacterized stressors such as the CO2 air emissions from combustion (in kg) or the employment hours of high-skilled females (in M.hr) are included in the so called satellite account. The impacts account indicates characterized stressors like the total greenhouse gas emissions (in kg CO2 eq.) or total employment (in 1000 p.).[5] In total the EXIOBASE dataset

[4]The seven final demand sectors consist of ¨Final consumption expenditure by households¨, ¨Final consumption expenditure by non-profit organisations serving households (NPISH)¨, ¨Final consumption expenditure by government¨, ¨Gross fixed capital formation¨, ¨Changes in inventories¨, ¨Change in valuables¨ and ¨Exports: Total (fob)¨.

[5]One can think of the satellite account containing the raw data, for example on all the

includes 1113 different uncharacterized stressors in the satellite account and 126 characterized stressors in the impacts account.

By using this additional data in combination with the standard Leontief demand model, one can calculate a consumption based emissions account, a production based account as well as accounts for emissions embodied in the import and export of different products. The consumption based account contains the total emissions (or often called footprints) of each product consumed by some final demand sector y in a certain region contained in Y. It can be calculated as:

$$CBA = S(I - A)^{-1}y \tag{1}$$

where S is a matrix containing the so-called stressor coefficients, i.e. the total emissions per monetary unit of output produced in a certain region (see vector x). The total footprints per region i can then be calculated from CBA by summing over the m footprints per sector and by including the impacts associated with the final use phase of the respective region. This can be done by adding the stressors occurring due to the final consumption F_Y for all w final demand categories of that region[6]:

$$CBA^i = \sum_{s=1}^{m} CBA_s^i + \sum_{c=1}^{w} F_{Y_c}^i \tag{2}$$

This method therefore captures the indirect environmental impact that occurs along the supply chain and during the production process and accounts it to the country in which the product is ultimately consumed. Summing up, the EXIOBASE environmentally extended supply-use tables allow to calculate the total consumption footprint associated with the consumption of 200 different products in 49 regions of the world.

Alternatively, one can use the production based account to calculate the production based (territorial) footprint of a region. It captures only the direct emissions and involved resources that are associated with the production process of products within a specific region. It does not take into account whether those products are ultimately consumed in this country or whether they are exported into other regions.[7] There are already several studies that compare the different approaches to the accounting of carbon emissions, see Ferng (2003) or Peters (2008). The discussion evolves around the decision of whether consumers or producers should ultimately be held accountable for generated carbon emissions. The use of a production- or consumption-based approach also influences the objectives of countries' pollution prevention measures and the evaluation of such achievements. In the following we want to concentrate on the consumption based account as our

different greenhouse gases like carbon dioxide or methan. The impacts account then combines this data according to a certain metric, e.g. the GWP100, to indicate the greenhouse gas footprint of products in kg CO2-equivalents.

[6]These so-called *direct emissions* are directly associated with households of a region, such as the consumption of heating fuels at home or the use of petrol while driving a car.

[7]The calculation of the production based account, import and export accounts as well as a more detailed explanation of the mathematical derivation is provided by Stadler (2021).

focus is on the analysis of the environmental impact of private household's consumption.

2.2 The European Commission's household budget survey

There are several datasets on household level consumption expenditure. One of the largest of these datasets is the European Household Budget Survey (HBS). The HBS consists of a series of national consumption expenditure surveys conducted by member states of the European Union (EU) and some other European countries. Its main focus is households' private consumption expenditure on goods and services. In addition, the survey contains some information on the households and the persons living in it, such as their demographcs, income and other socio-economic characteristics. The survey results are mainly used to compile and update the weights for the Consumer Price Indices (CPI) or other macroeconomic indicators.

The first survey was conducted by most EU Member States in the early 1960s. Frequency and timing of the national surveys vary slightly from country to country, but new data are generally available every five years since 1988. The two most recent rounds of surveys took place in 2015 and 2020. More detailed information can be found at Eurostat (2015). We use the HBS for 2015 for our matching procedure and the analysis. An overview of the participating countries of the HBS in this year is provided in Table A.1.

Participating households are asked to record their expenditures over a specified period, which can range from one week (e.g. in France) to three months (e.g. in Germany). The type of recording, electronically and/or in paper form, also differs across countries. Households consumption expenditure is then provided according to the 5-Digit COICOP classification, which has been in effect since 2013, and reported in purchaser's prices. Since the survey data is only collected over a sample of the entire household population, sample weights are then used to construct representative statistics for the respective country's population. This allows to derive variables such as the mean consumption expenditure or corresponding ghg emission footprint of a country. Eurostat (2016) provides a more detailed description of this procedure. In total, the HBS provides detailed information on 277,200 households. The number of included observations per country is shown in Table A.2. It also contains the number of observations that are dropped in the matching and data cleansing process, which we will go into more detail about in section 2.3.

2.3 Matching process of aggregate and individual level data

One goal of this study is to construct an internationally comparable dataset on the individual consumption footprint. There are a few studies that combine environmentally augmented input-output data with individual level consumption data to derive a measure of the individual carbon footprint, see Sager (2019),

Hardadi et al. (2021), Jacksohn et al. (2023), Büchs and Schnepf (2013), Ivanova et al. (2016), Ivanova et al. (2017) or Duarte et al. (2021). These studies provide important foundations for this paper, but they are mostly carried out for only one country each. As different matching algorithms between individual level and aggregate level data were used, it is hard to compare them across countries. Exceptions are Büchs et al. (2021) and Duarte et al. (2021), who study the carbon footprints of households in EU countries, but the matching of EXIOBASE and the EU household budget survey in Büchs et al. (2021) is only based on very crude consumption categories. We set up the matching between individual level consumption data and aggregate level emissions on a much finer definition of production-consumption categories. In this regard it is similar to Duarte et al. (2021) or Ivanova and Wood (2020), but it includes an even broader range of categories for food and for energy products used in the residential sector, like electricity, gas and liquid or solid fuels.

In the following we describe the procedure to match the data from the EXIOBASE with the data from the HBS. As an rather obvious restriction our matching procedure is limited to countries represented both in the EXIOBASE dataset and the European Comission's HBS. This includes the 27 EU member states for 2015, as well as the United Kingdom, Turkey and Norway. Table A.1 summarizes the countries covered in the two databases. We only included the EU27 in our final matching procedure and following analysis.

A key challenge for the data work in this study was to match the aggregate data on greenhouse gas emissions by product category from the EXIOBASE project with individual level data on consumption expenditure. This matching required to translate the 200 product categories contained in the environmentally augmented input-output tables into consumption categories included in the COICOP consumption purpose classification. For some goods and services this was quite easy, like for rice, milk or eggs as well as for financial or educational services. The matching of some other products required more sophistication, for example the product "Gas/Diesel Oil", which is used for both driving cars and heating homes. We assigned each product in EXIOBASE to one consumption category based on its predominant use, which is the procedure that is applied in Büchs et al. (2021).[8] For example, one can assume that wood and wood products are predominantly used in the real estate construction sector. The alignment of the HBS classification system and the EXIOBASE products to the chosen matching categories is summarized in Table E.11. In total, we match the two datasets across 40 categories consisting of 13 main categories, such as ¨Food and Drinks¨ or ¨Transportation¨, that are further broken down into several subcategories. Those matching categories are displayed in Table 1.

[8] An alternative would be to use consumption interdependence tables for the matching between products and consumption purposes, as in Pothen and Tovar Reaños (2018) or Jacksohn et al. (2023).

Table 1: Overview Matching Categories

Code	Category
10	**Food and Drinks**
10.1	Food
10.11	Cereal, grains, crops and bread
10.111	Rice
10.112	Other cereal products
10.12	Meat
10.13	Fish and seafood
10.14	Milk and dairy products
10.15	Vegetable oils and fats
10.16	Vegetables, fruits and nuts
10.17	Sugar
10.18	Other animal products
10.19	Other food products
10.2	Beverages
10.3	Tobacco
20	**Housing Construction**
21	**Housing Energy**
21.1	Electricity
21.2	Gas
21.3	Liquid fuels
21.4	Solid fuels
21.5	Heat energy
22	**Housing Consumption**
30	**Purchase and maintenance of vehicles**
31	**Fuels and lubricants**
31.1	Diesel
31.2	Petrol
31.3	Other fuels and lubricants
32	**Transportation services**
32.1	Railway transportation services
32.2	Air transportation services
32.3	Sea and inland waterway transportation services
32.4	Other transportation services
40	**Hotels and Restaurants**
50	**Nondurable Consumption**
60	**Health**
70	**Education**
80	**Finance**
90	**Other Goods and Services**

2.3.1 Price transformation

The household expenditure in the HBS is in purchaser prices (*pp*) while EXIOBASE provides the final demand in basic prices (*bp*). For an accurate matching of the two datasets we convert the consumption expenditure of the HBS from purchaser to basic prices. We use the data on taxes minus subsidies t as well as trade and transport margins that are provided for each product and country by EXIOBASE. Trade and transport margins are then summed up in vector m. [9]

The conversion from purchaser to basic prices of product i in region c can be described as:

$$y_{ic}^{pp} = y_{ic}^{bp} + t_{ic} + m_{ic} \quad \Rightarrow \quad y_{ic}^{bp} = \left(1 - \frac{t_{ic}}{y_{ic}^{pp}} - \frac{m_{ic}}{y_{ic}^{pp}}\right) y_{ic}^{pp}. \tag{3}$$

First, we calculate the proportions of taxes less subsidies and of the trade and transport margins from EXIOBASE. We then substract those shares from the HBS consumption expenditure in purchaser prices. One option would be to caculate the average shares of net taxes and margins for each of the matching catagories. As taxes and margins vary significantly across products, the most accurate conversion would require to match each of the products in HBS by the respective EXIOBASE products. The second option would probably lead to a more accurate price adjustment, but would also be more time-consuming. We decided to apply the first option and made the adjustments by matching categories. We therefore make the assumption that net taxes and margins don't differ within countries and matching categories, which is a limitation in our dataset. Transport margins can be reallocated to expenditures for the respective transport service sector and therefore increase the emission footprint of those sectors. Trade margins were then counted as expenditure for the matching category "Other Goods and Services".[10] The corresponding expenditure share of net taxes minus subsidies, which can be both positive and negative, was excluded from the further matching process.

2.3.2 Calculation of emission footprints

Once we have recalculated the HBS data into basic prices we dropped all observations with reported negative consumption expenditure entries. This was the

[9] Net taxes are provided as part of the impact account as ¨Taxes less subsidies on products purchased: Total¨. The EXIOBASE products ¨Retail trade services of motor fuel¨ and ¨Wholesale trade and commission trade services, except of motor vehicles and motorcycles (51)¨ are considered as part of the trade margins. The products ¨Railway transportation services¨, ¨Air transport services (62)¨, ¨Sea and coastal water transportation services¨, ¨Inland water transportation services¨, ¨Other land transportation services¨ and ¨Transportation services via pipelines¨ are counted as part of the transport margins.

[10] More specifically, during the price transformation the trade margins were allocated to the Exiobase products "Wholesale trade and commission trade services, except of motor vehicles and motorcycles (51) and "Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods (52)".

case for 1079 out of the 270200 observations, as can be seen in Table A.2. We also encountered the problem that in some countries and for some categories the sum of expenditure reported for subcategories did not add up to the expenditure reported for the main category. For households with such discrepancies we distributed the difference to the subcategories according to their expenditure share of the main categories expenditure.[11] We assumed that the reported expenditure in the main category is true and adjusted the respective subcategories. This was the case for 8,865 households (excluding Germany, for which a special proceedure was applied). For almost all of those households the main category expenditure was greater than the sum of subcategory expenditures. In 284 cases for Greek it was the other way around. Table A.2 contains an overview of the number of observations per country for which we adjusted the expenditure. Furthermore, in some cases, the households reported positive main category expenditure and zero expenditure in all subcategories. This was the case for 51006 households, of which the large majority with 50404 observations is from Germany with 602 from other countries, see Table A.2. We dropped all of those observations except those from Germany. The problem of the missing german data was handled differently and is described in more detail in section 2.4.2.

We then derived product and region specific indirect GHG emission intensities based on the CBA and final demand data provided in EXIOBASE, using the averages for the years 2011 to 2015[12]. The calculated indirect emission intensities are given in kg CO2 eq. per million Euro. As EXIOBASE does not differentiate between the final demand of different regions within one country we can only generate the emission intensities per country.

We supply the total emission footprint as well as both direct and indirect emissions associated with household's expenditure separately. EXIOBASE reports direct emissions only per total final demand of households for each country. There are different mechanisms to deal with this and to distribute the total direct emissions per country to each product category. We have decided to distribute them according to the proportion of expenditure on the respective product in relation to total household final demand of each country. An alternative method was to distribute them according to the calculated indirect emission intensities, which simply scales the total GHG emissions up without changing their distribution across the households consumption basket. As the results using both methods were similar, we decided to use the more common way to distribute them according to the expenditure shares. The indirect and direct carbon footprints of the matching categories are then generated by multiplying the emission intensi-

[11] To rule out small errors due to rounding we only considered differences greater than 5€ to be a discrepancy that we need to handle.

[12] Note that if the term GHG emissions is used in the following, it refers to the greenhouse gas emissions according to the Global Warming Potential (GWP100) that are available as part of the impact account of EXIOBASE. The GWP100 metric is used to convert different greenhouse gases like carbon dioxide, methane, nitrous oxide and sulphur hexafluoride to kilograms CO2-equivalents (kg CO2 eq.) according to Solomon et al. (2007).

ties with the respective consumption data from the HBS 2015. Total household greenhouse gas emissions are then given as the sum of both direct and indirect greenhouse gas emissions.

2.4 Special cases

2.4.1 Product allocation

Certain assumptions had to be made in order to match the product categories at this level of detail. The first adjustment was made in terms of the EXIOBASE product classification ¨Gas/Diesel Oil¨. This product cannot be clearly contributed to only one category, because it is typically used both as an fuel of the main category ¨Transportation¨ as well as for heating purposes, which would correspond to the category ¨Household Energy¨. The emissions associated with the household final demand of ¨Gas/Diesel Oil¨ were therefore distributed among the household energy subcategory ¨Liquid Fuels¨ (21.3) and the transportation subcategory ¨Diesel¨ (31.1). This was done using the gas oil and diesel consumption ratios generated from the HBS 2015 data.[13] As a second adjustment the emissions corresponding to the household final demand of the EXIOBASE product classification ¨Retail trade services of motor fuel¨ were distributed among the three subcategories ¨Diesel¨, ¨Petrol¨ and ¨Other Fuels and lubricants¨ (31.1-31.3). This was done according to their respective proportion of the total emissions of the ¨Fuels and Lubricants¨ category (31). Finally, emissions corresponding to the final demand "Rubber and plastic products (25)" were distributed among the category "Housing Consumption" (22) and the transportation subcategory "Purchase and maintenance of vehicles" (30), where rubber products are also used in the form of tires for vehicles.

2.4.2 Germany, Estonia, France, Czech Republic, Sweden

We adjusted the household weights in HBS for size in the Czech Republic before the matching procedure, as the number of households varied greatly from the reported statistics of Eurostat after an aggregation was applied.

Another adjustment was made for the ¨Fuels and Lubricants¨ category of the countries Estonia, France, Germany and Sweden. For those three countries the emissions associated with the transportation fuel ¨Diesel¨ were zero, which is a rather unrealistic assumption and possibly due to data discrepancies. For each country the respective emissions of this category were distributed across the three subcategories in relation to their average emission distribution across all other countries.

In the case of the data for Germany we needed to make some further adjustments, due to missing data of food consumption. For Germany the original dataset con-

[13] For this we made the assumption that the price ration of diesel over gas oil is 1,6.

tained only the expenditure for the main category food, while the reported expenditure was zero for all food subcategories. This was also partially true for the main categories housing energy and transportation services, for which the subcategory expenditure of approximately half of the german observations was missing. To generate a complete dataset for all 27 EU countries we imputed data on the composition of german household expenditure on food from the German Income and Expenditure Survey ("Einkommens- und Verbrauchsstichprobe,EVS") for 2013.

We regressed the consumption expenditure of the seven subcategories of food using the following regression equation:

$$\begin{aligned}\text{subcat}_{cj} =& \beta_0 + \beta_1 \text{exp10.1}_j + \beta_2 \text{exp10.2}_j + \beta_3 \text{exp10.3}_j + \beta_4 \log(\text{inc}_j) \\ &+ \beta_{5k} \text{nuts1}_{kj} + \beta_6 \text{hsize}_j + \beta_{7m} \text{gender}_{mj} + \beta_{8l} \text{maritalstatus}_{lj} \\ &+ \beta_{9p} \text{occup}_{pj} + \beta_{10q} \text{active}_{qj} + \beta_{11r} \text{age5}_{rj} + \epsilon_i\end{aligned}$$

The dependent variable, subcat_{cj}, represents the expenditure for a specific food subcategory $c \in \{10.111, 10.112, 10.12, \ldots, 10.18\}$ of household j. exp10.1_j corresponds to the household expenditure for the main category of food, while exp10.2_j and exp10.3_j denote the household expenditure for the main categories of beverages and tobacco, respectively. The term $\log(\text{inc}_j)$ represents the logarithm of income. Dummy variables for NUTS1 regions in Germany are denoted as nuts1_{kj}, and hsize_j captures the household's size. Gender is represented by dummy variables gender_{mj}, and marital status is indicated by recoded categorical variables $\text{maritalstatus}_{lj}$. Dummy variables occup_{pj} specify the type of occupation of the household's reference person, while active_{qj} captures the number of economically active persons per household. Finally, age5_{rj} represents dummy variables for 5-year age groups, and ϵ_j is the error term. Mapping category 10.18 was treated as the residual category, so it contains the difference of expenditure in category 10.1 and the sum of all other estimated subcategories. This imputation process was applied before the price adjustment and calculation of household's greenhouse gas emissions. This allowed us to generate a complete dataset of household greenhouse gas emissions for all 27 EU countries.

2.5 Data cleansing and sample selection

To mitigate the influence of outliers in our analysis, we excluded observations with extreme values in consumption expenditure. Specifically, we excluded observations in the bottom and top 1% of the distribution of equivalized consumption expenditure per country. Equivalized consumption expenditure was generated using the OECD equivalence scale in order to take account of differences in the households composition and to ensure comparability between households. Additionally, in the parts of our analysis that focus on income, we further restricted

the sample by excluding observations with negative income.[14] The observations that are dropped as part of the data cleansing process are summerized in Table A.2.

3 Exploratory analysis of greenhouse gas emissions

We start by documenting the key features of the distribution of greenhouse gas (GHG) emissions in our sample. Household-level emissions are linked to consumption behavior. Panel (a) of Figure 1 illustrates the expenditure share across 13 main consumption components for the pooled sample of all EU households. The four largest components of total household consumption expenditures are food, housing construction (including rents), nondurable consumption, and other goods and services. The remaining consumption components account for around five percent of household consumption expenditure each. The picture changes significantly when we examine the GHG emissions associated with these 13 consumption components, as shown in panel (b) of Figure 1.[15] On average, a typical EU household emits approximately 18 tons of greenhouse gases per year, measured in CO2 equivalents. Housing energy, fuels and lubricants, and transportation services play a prominent role in these emissions. Food also is a major contributor. Specifically, 21 percent of the average household's carbon footprint is due to food consumption, 34 percent is related to housing, and 20 percent to transportation. Consequently, food, housing, and transport together account for about three-quarters of the household's carbon footprint.

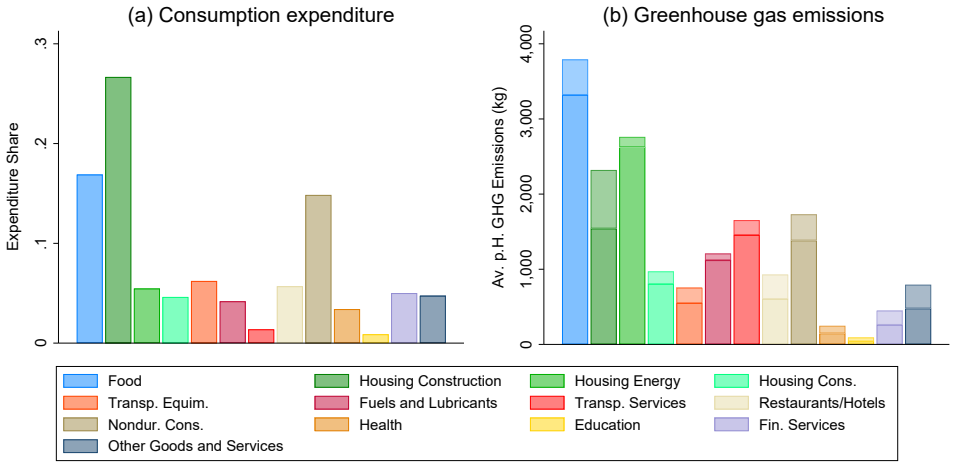
Panel (b) of Figure 1 divides the total emissions of each consumption component into indirect emissions (darker shading) and direct emissions (lighter shading). Indirect emissions are those outside the immediate control of households. They include all emissions generated in the production process of goods and services, starting from the raw inputs at the beginning of a supply chain to the final goods producer. Using the common notion of firm emissions classifications, indirect emissions represent upstream scope 2 and 3 emissions. Direct emissions, on the other hand, are those under the immediate control of the household. They are directly linked to the consumption process, such as the burning of wood to heat an oven in a house. As panel (b) of Figure 1 reveals, most of the emissions associated with the final private consumption of goods are indirect emissions, constituting around 80% of total emissions. Direct emissions play a much smaller role.

Emissions are attributed only to households that purchase polluting goods and services. Therefore, the greenhouse gas (GHG) emissions associated with any consumption component can be expected to have both an extensive margin (whether emissions are present or not) and an intensive margin (the emissions intensity per unit of spending). To illustrate the importance of both margins, panel (a) of

[14] When we use the term income we mean net income, so total monetary income from all sources minus income taxes.

[15] The data behind this figure are shown in Table B.3 in Appendix B.

Figure 1: Household level greenhouse gas emission in the EU (pooled sample)



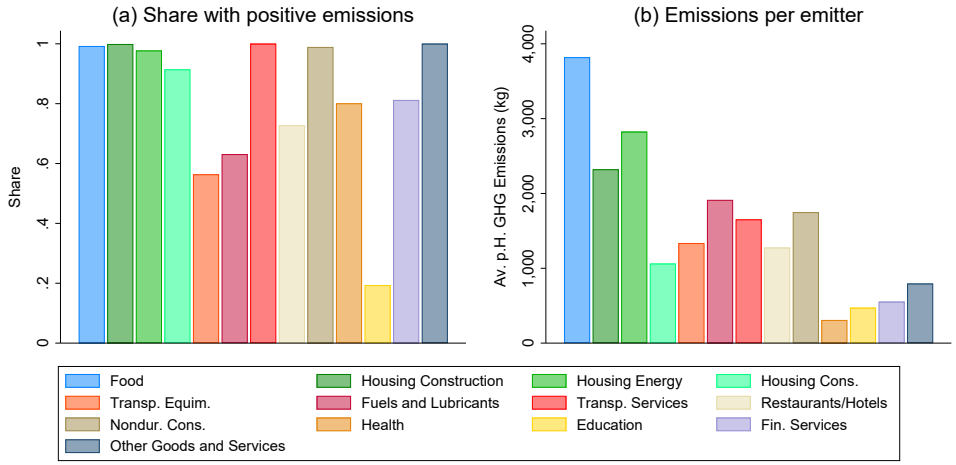
Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Panel (a): average expenditure on different consumption components relative to average total household spending. Panel (b): average per household GHG emissions associated with each consumption component. Darker shading indicates indirect emissions and lighter shading indicates direct emissions associated with each consumption component.

Figure 2 shows the share of EU households that generate positive GHG emissions through any of the 13 consumption components. Unsurprisingly, almost all households have positive GHG emissions related to food, real estate, transportation services, non-durable consumption, and other goods and services. However, not all households own vehicles, resulting in only 50 percent of households reporting expenditures on transportation equipment and fuels and lubricants. Additionally, a quarter of households report zero spending on restaurants and hotels, health services, and financial services. The most notable category is education, where only about 20 percent of households report any positive spending, thereby generating GHG emissions. Knowing how many households have positive emissions in each spending category allows us to calculate the average emissions per emitter, as shown in panel (b) of Figure 2. For universal spending categories, emissions per emitter are identical to average emissions per household, as seen in panel (b) of Figure 1. However, average emissions per emitter are about twice as high as average household emissions for transportation equipment and fuels and lubricants, and five times as high for education. In summary, when considering the cross-sectional inequality of household GHG emissions, an important distinction may be whether households generate GHG emissions through a particular consumption component at all.

3.1 Between-country variation in footprints

The primary objective of this paper is to examine the inequality in carbon emissions across the European Union. There are two key dimensions to consider:

Figure 2: Extensive vs. intensive margin emissions

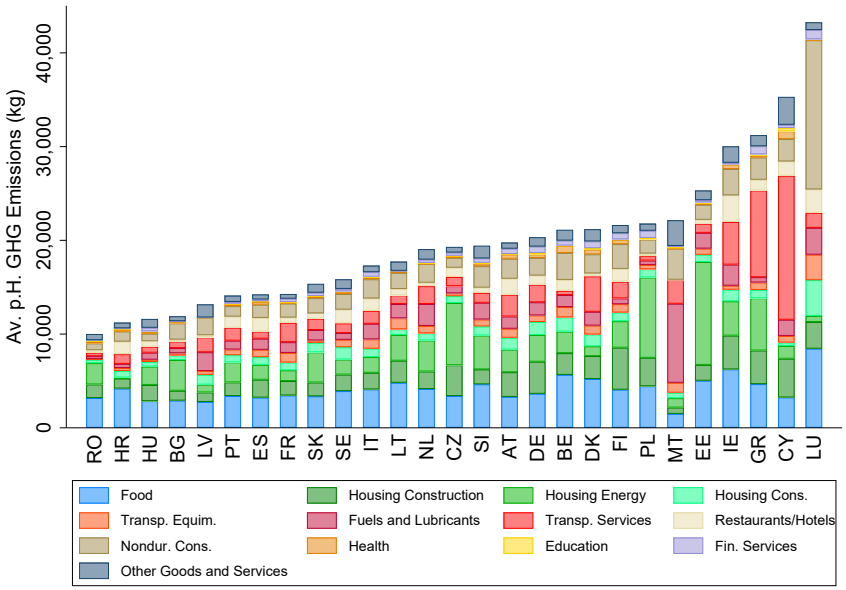


Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Panel (a): share of households with positive GHG emissions related to the different consumption componens. Panel (b): average per household GHG emissions for those households with positive emissions.

between-country and within-country inequality in greenhouse gas emissions. To illustrate the former, Figure 3 presents average emissions per household in the 27 EU countries. The average carbon footprint for the entire EU is approximately 18 tons of CO2-equivalent emissions. Yet, our data reveal significant variation in average household carbon footprints across the different countries. For instance, GHG emissions range from about 10 to 12 tons per household in Romania, Croatia, Hungary, Bulgaria, and Latvia, to over 25 tons per household in Estonia, Ireland, Greece, and Cyprus. Notably, Luxembourg has an average household carbon footprint of nearly 45 tons.

When looking at the individual components of the carbon footprint, the most significant differences in GHG emissions across countries are related to housing, particularly housing energy, and transport. The Czech Republic, Poland, and Estonia are among the highest emitters of greenhouse gases from housing energy. Conversely, in Croatia, Latvia, France, Denmark, and Malta, housing energy only has minimal impact on the average household carbon footprint. Transportation plays a crucial role in defining the carbon footprint of Malta, Ireland, Greece, and Cyprus, where waterway transport is integral to daily life. Compared to these substantial differences, the carbon footprint associated with food and other nondurable consumption is relatively uniform across countries. The only exception from this is Luxembourg, where emissions related to food and nondurable consumption are extraordinarily large.

Figure 3: Average emissions across EU countries



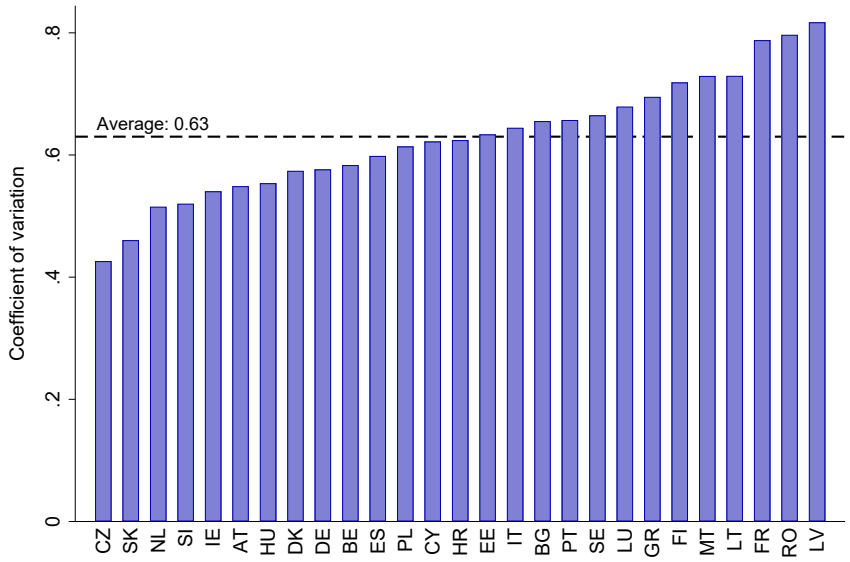
Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Figure shows average per household GHG emissions for each country, divided by the different consumption categories.

3.2 Within-country variation in footprints

While between-country inequality in GHG emissions can be measured using aggregate data, the advantage of a micro dataset is that it allows for the investigation of within-country inequality. As a first step towards analyzing individual-level carbon footprints, Figure 4 shows the coefficient of variation of household-level GHG emissions in all our sample countries. The coefficient of variation, which is the standard deviation divided by the mean, measures the variability in carbon footprints between households relative to a country's average emissions. The average coefficient of variation across all sample countries is 0.63. This implies that an increase of one standard deviation in the distribution of household-level carbon footprints corresponds to a 63% higher emissions level. Generally, the within-country variability of household-level emissions is substantial and not necessarily related to a country's average emissions. For instance, Romania and Latvia exhibit relatively small average household carbon footprints but have some of the highest variability, nearly 80%. In contrast, Luxembourg has the largest average household GHG emissions, yet its within-country variability is close to the average.

To understand the variability in household-level GHG emissions, it is useful to decompose the within-country variance in household-level emissions F_{total} into the variability stemming from the 13 different consumption components F_k. The

Figure 4: Coefficients of variation of GHG emissions across EU countries



Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Figure shows the coefficient of variation, i.e. the standard deviation divided by the mean for each country.

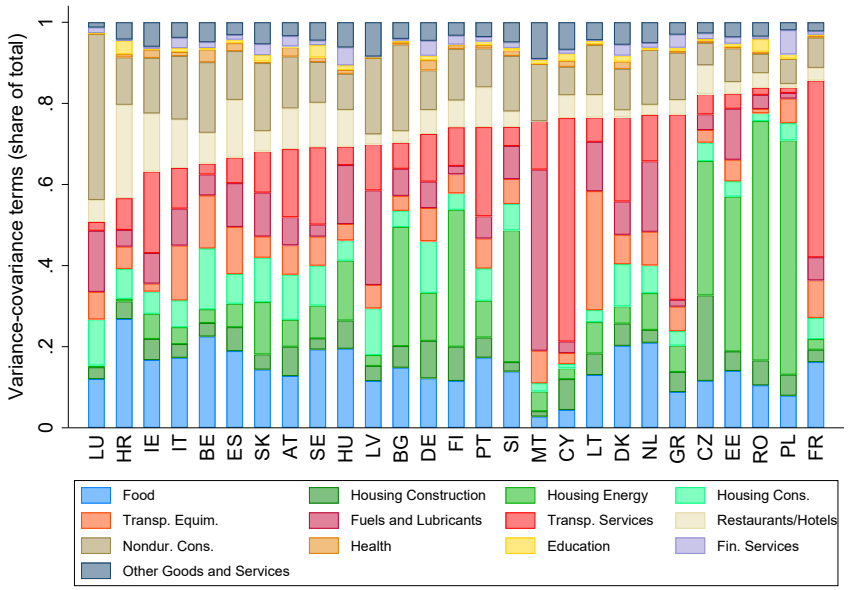
variance of the household-level carbon footprint can be expressed as:

$$\mathrm{Var}(F_{total}) = \sum_j \Bigg[\underbrace{\mathrm{Var}(F_j) + \sum_{k \neq j} \mathrm{Cov}(F_j, F_k)}_{=:\mathrm{VCov}(F_j)} \Bigg].$$

In this decomposition, each component F_j is attributed its own variance $\mathrm{Var}(F_j)$ as well as its covariances with all other components $\mathrm{Cov}(F_j, F_k)$. The sum of these two is referred to as the variance-covariance terms of the emissions F_j related to a consumption component j. Figure 5 shows the variance-covariance terms of household-level GHG emissions related to any of the 13 consumption components as a share of the total variance in individual footprints for each sample country. The majority of the variance in household-level carbon footprints – ranging from 60% to 85% – is related to the consumption of food, real estate (including housing energy), and transportation. The importance of these consumption components varies across countries. For example, housing energy plays a significant role in Bulgaria, the Czech Republic, Estonia, Finland, Poland, and Romania. Conversely, transportation is a major factor explaining the between-household variance in carbon footprints in Cyprus, France, Greece, Latvia, and Malta.

The decomposition of emissions from different consumption components in Figure 5 is incomplete because the covariance terms are simply included with each consumption component. In fact, when we examine the importance of covariance terms (see Figure B.1 in Appendix B), we find that the covariance terms

Figure 5: Variance-covariance terms related to different consumption components



Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Figure shows the variance-covariance terms of household-level GHG emissions related to each of the 13 consumption components as a share of the total variance of household-level GHG emissions.

between different components typically account for around 60% of the total variance. This suggests that the different consumption components cannot be viewed in isolation. Instead, the data should be reducible to a smaller set of important components. To achieve this, we conducted a principal components analysis of the within-country variation in household carbon footprints for the pooled sample of countries, see Table 2.[16] Consistent with our prior assessment, we find that housing, including energy (C3), and transportation (C2 and C4) play significant roles in determining household-level carbon footprints. Furthermore, there is a strong major component (C1) that explains around 25% of the total variation in household GHG emissions in a given country. This component encompasses all forms of non-durable consumption, including food, non-durable consumption related to housing, transportation services, hotels and restaurants, other non-durable consumption, and other goods and services. Finally, as suggested by the analysis of extensive versus intensive margins in Figure 2, both health (C5) and education (C6) form a principal component that is orthogonal to any other consumption behavior.

[16]The details of the principal component analysis are discussed in Appendix B.2.

Table 2: Principal components of within-country emissions inequality

	C1	C2	C3	C4	C5	C6
Proportion	0.25	0.08	0.08	0.08	0.07	0.07
Cumulative prop.:	0.25	0.33	0.40	0.48	0.55	0.62
Eigenvalue	3.19	1.03	0.99	0.98	0.95	0.88
Varimax rotated component loadings:						
Food	0.30	0.21	0.03	−0.14	0.16	−0.01
Housing Construction	0.22	−0.18	0.54	−0.05	−0.03	−0.01
Housing Energy	−0.07	0.07	0.82	0.01	0.00	0.00
Housing Cons.	0.39	−0.08	−0.05	−0.11	0.13	−0.18
Transp. Equim.	0.00	0.02	0.00	0.95	0.02	−0.02
Fuels and Lubricants	0.09	0.64	−0.10	−0.03	−0.08	−0.05
Transp. Services	0.40	−0.20	−0.02	0.23	−0.07	0.06
Restaurants/Hotels	0.40	0.02	−0.09	−0.05	−0.23	0.12
Nondur. Cons.	0.46	0.06	−0.03	−0.01	0.03	0.05
Health	0.00	−0.01	−0.01	0.02	0.94	0.03
Education	0.00	0.00	0.00	−0.01	0.03	0.97
Fin. Services	−0.08	0.66	0.13	0.07	0.02	0.04
Other Goods and Services	0.40	0.12	0.06	0.09	0.04	−0.04

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied. Household weights were adjusted such that the weights in each country sum up to the same number. In addition, carbon footprints in each country were standardized by average footprints in each country to account for cross-country variation in average household emissions. The results of the principal component analysis consequently isolate pure within-country inequality.

3.3 Discussion of results

Our exploratory data analysis reveals important insights into carbon inequality in the European Union. First and foremost, the dominant sources of household-level carbon emissions are related to the consumption of food, housing (including housing energy), and transportation. These three components are crucial in defining (i) the average carbon footprint of a typical EU household, (ii) cross-country variation in average household footprints, and (iii) within-country variation in household-level GHG emissions. Second, carbon inequality is significant. There is considerable variation in the average household carbon footprint across countries, with average emission levels ranging from 10 tons per year in Romania to almost 50 tons per year in Luxembourg. Additionally, we find substantial within-country variation in GHG emissions across households, with an average coefficient of variation of around 60%.

These findings are important for the political economy of carbon pricing. Individual countries within the EU might resist carbon pricing for two reasons: either because they fear that their households generally induce a lot of emissions through their consumption behavior and are therefore disproportionately burdened by car-

bon prices relative to households in other countries, or because carbon emissions are distributed quite unequally within their country, and carbon pricing may consequently induce additional inequality. Interestingly, these two features do not always coincide. For example, average household-level carbon emissions are below average in France and Romania, but these two countries have some of the highest carbon inequality. Conversely, Ireland has one of the largest average household carbon footprints, but emissions are distributed much more equally within the country.

4 Emissions inequality between and within countries

The previous results demonstrated considerable inequality in household GHG emissions both between and within countries. But which dimension is more important? In this section, we aim to quantify the importance of between- and within-country variation in carbon footprints more formally. Our preferred measure of inequality is the generalized entropy (GE) index. This class of indices allows us to summarize inequality in a population with a single number. Different versions of the index focus on inequality in various parts of a distribution. The $GE(0)$ emphasizes inequality at the bottom of the distribution, while the $GE(2)$ highlights top inequality. Our measure of choice, the $GE(1)$, focuses on inequality in the center of a distribution, just like the Gini index. Formally, the $GE(1)$ index of the household carbon footprint F_i in a population of individuals $i \in \mathcal{N}$ with total size $N = |\mathcal{N}|$ is given by:

$$GE(1) = \frac{1}{N} \cdot \sum_{i \in \mathcal{N}} \frac{F_i}{\bar{F}} \cdot \log\left(\frac{F_i}{\bar{F}}\right).$$

$\bar{F}$ denotes the population average of F_i in the population $\mathcal{N}$. Figure C.2 in Appendix C shows the relationship between the Gini index and the $GE(1)$ index of household-level GHG emissions for each sample country. The two indices yield the same results, meaning that countries are ranked in the same order according to both indices. A simple linear regression between the two indices has an explained variance of $R^2 = 0.98$.

Let us now divide the population $\mathcal{N}$ into G different subgroups $\mathcal{N}_g$ such that $\mathcal{N}_1 \cup \mathcal{N}_2 \cup \ldots \cup \mathcal{N}_G = \mathcal{N}$. The size of each subgroup is denoted by $N_g = |\mathcal{N}_g| > 0$. We can then decompose the $GE(1)$ index as follows:

$$GE(1) = \underbrace{\sum_{g=1}^{G} \omega_g \cdot \frac{\bar{F}_g}{\bar{F}} \cdot GE_g(1)}_{\text{within-group inequality}} + \underbrace{\sum_{g=1}^{G} \omega_g \cdot \frac{\bar{F}_g}{\bar{F}} \cdot \log\left(\frac{\bar{F}_g}{\bar{F}}\right)}_{\text{between-group inequality}},$$

where $\omega_g = \frac{N_g}{N}$ is the relative size of population subgroup g, $\bar{F}_g$ is the average carbon footprint in subgroup g, and $GE_g(1)$ is the $GE(1)$ index for subgroup g. Consequently, the $GE(1)$ index can be broken down into two components. First, a

within-group inequality component that is composed of the (weighted) inequality indices of household GHG emissions in each subgroup g. Second, a between-group component that measures differences in the average household footprint across different countries.

We exploit the decomposition property of the $GE(1)$ index to examine inequality in household carbon footprints within the entire EU. To this end, we calculate the total $GE(1)$ index, assuming that each country forms one subgroup. The results of this decomposition for total household GHG emissions, as well as selected consumption components, are shown in Table 3. There are two key points to note. First, within-country inequality is generally larger than between-country inequality. This is true for the total household carbon footprint, where within-country inequality accounts for almost 85% of the total variation in household GHG emissions across the entire EU. It is also true for subcomponents related to the consumption of food, housing energy, and transportation. Second, inequality in total footprints is substantially smaller than the inequality of GHG emissions related to the consumption of housing energy and transportation. Higher inequality in these particular components stems from both larger between-country inequality and larger within-country inequality. The fact that these high levels of inequality add up to a much smaller inequality in overall footprints suggests a negative correlation in the consumption of these two components across households. For the between-country component, this was already suggested by the result presented in Figure 3. In Section 5, we will investigate heterogeneity in household consumption baskets within countries more thoroughly.

Table 3: Inequality decomposition between- and within country

		decomposition		share
	$GE(1)$	within	between	within
Total footprint	0.196	0.166	0.030	0.846
Food	0.228	0.215	0.013	0.945
Housing energy	0.582	0.352	0.230	0.604
Transportation	0.535	0.403	0.132	0.754

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

In the discussion around the coefficient of variation of GHG emissions in different EU countries (see Figure 4), we observed that high inequality in household-level GHG emissions within a country does not necessarily correspond to a high average household carbon footprint. We want to elaborate on this finding. Specifically, we split countries according to two criteria: first, whether their average household carbon footprint is below or above the median; and second, whether their inequality level in household GHG emissions is below or above the median. This results in the four different country classifications shown in Table 4. Surprisingly, our

data shows a negative relationship between average carbon footprints and footprint inequality. There is a substantial number of households on the off-diagonal of this classification scheme, suggesting that high average footprints tend to be associated with low inequality and vice versa.

Table 4: Average footprint and footprint inequality

Average HH footprint	Footprint inequality $GE(1)$: low	Footprint inequality $GE(1)$: high
low	Hungary, Slovakia, Slovenia, Spain	Bulgaria, Croatia, France, Italy, Latvia, Lithuania, Portugal, Romania, Sweden
high	Austria, Belgium, Cyprus, Czech Republic, Denmark, Germany, Ireland, Netherlands, Poland	Estonia, Finland, Greece, Luxembourg, Malta

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

This result is somewhat counterintuitive compared to what we observe when examining the properties of the net household income distribution. When we apply the same classification to price-level-adjusted net household income, see Table C.5 in Appendix C, we find a substantial positive correlation between averages and inequality measures. This means that countries with higher net income inequality also tend to have higher average net incomes.[17] There can be multiple reasons for this, one of which certainly has to do with the extent of fiscal redistribution. But why does this relationship invert when looking at household GHG emissions?

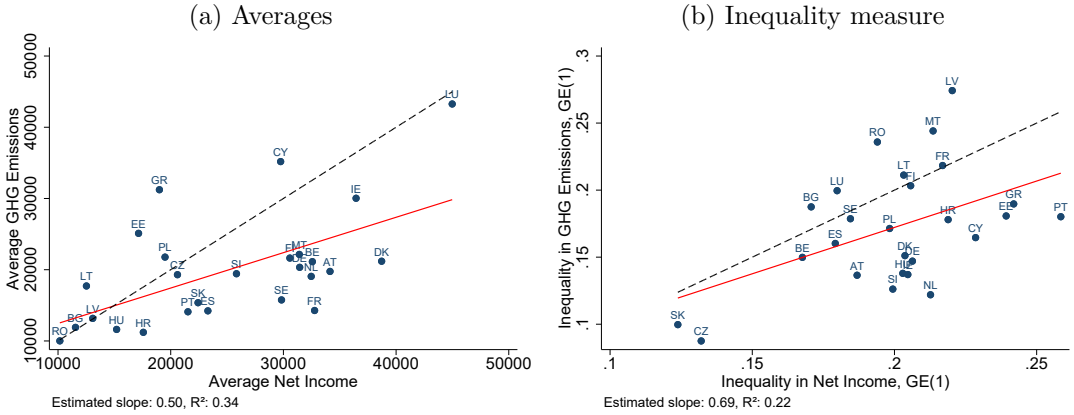
From a technical point of view, there can only be two sources of this phenomenon: either average net income is not a good predictor of average household GHG emissions, or income inequality is not strongly related to inequality in carbon footprints. To shed light on this, Figure 6 shows cross-country scatter plots of average net income and average household GHG emissions (Panel a) and income inequality and emissions inequality (Panel b). The red lines indicate a simple linear regression line, while the dashed lines show the 45-degree line as a reference point. Both plots generally show a positive association between incomes and emissions, as evident from the slope of the regression lines. This means that countries with higher average incomes tend to exhibit higher household GHG emissions, and countries with more income inequality tend to have higher inequality in household carbon footprints.[18] However, the relationship is relatively weak, as measured by the explanatory power of the simple regressions. A linear regression can only explain

[17] The same is true for household consumption; see Table C.6 in Appendix C.

[18] The latter relationship is somewhat biased by the Czech Republic and Slovakia. Eliminating

34 percent of the variance in average GHG emissions across countries and only 25 percent of the variance in inequality.[19] This indicates that there is considerable variation in household-level carbon footprints that is unrelated to income.

Figure 6: Correlation of emissions and household net income



Estimated slope: 0.50, R^2: 0.34 Estimated slope: 0.69, R^2: 0.25

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied. Italy was excluded from the sample, as no income data is available. The measure of income is price-level adjusted total household monetary net income.

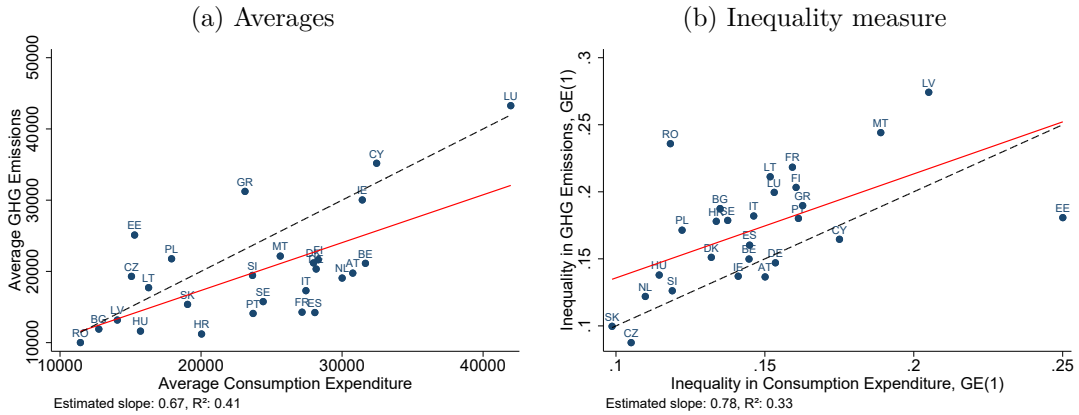
One reason for the weak relationship between household income and household carbon emissions may be that emissions are more closely associated with household consumption rather than income. In Figure 7, we repeat the same analysis but use price-level-adjusted household total consumption instead of income. Using consumption instead of income increases the R^2 values somewhat, but the majority of cross-country variation in average household footprints and carbon footprint inequality cannot be explained by systematic variation in net incomes or consumption. This suggests that, in a cross-country setting, household carbon emissions are predominantly shaped by the structure of consumption baskets and the emissions intensity of different consumption components and not by consumption or income levels.

To sum up this section, our analysis has delivered several important insights. First, the majority of inequality in household-level GHG emissions arises within countries rather than between them. Second, inequality in emissions related to the consumption of housing energy or transportation is substantially larger than total household GHG emissions. This suggests a negative correlation structure for at least these two components, both across and within countries. Third, unlike income or consumption inequality, there is a negative relationship between the average and the inequality of household GHG emissions across countries. More

these two from the graph would significantly weaken the relationship between income inequality and emissions inequality.

[19]Note that a non-linear regression is not expected to significantly improve the fit of the data.

Figure 7: Correlation of emissions and household consumption expenditures



Estimated slope: 0.67, R^2: 0.41 Estimated slope: 0.78, R^2: 0.33

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied. The measure of consumption is price-level adjusted total household consumption expenditure.

generally, the cross-country relationship between net household income and household GHG emissions is quite weak, both in terms of household averages and inequality measures. The same is true for average household consumption. This suggests that the composition of the consumption basket as well as the emission intensities associated with certain consumption components are a main driver of cross-country variation in household-level greenhouse gas emissions.

5 The income-emissions relationship

The previous section focused on cross-country differences in household GHG emissions. In this section, we investigate the household carbon footprint within countries. As a first step, Table 5 presents regression results of household income on household GHG emissions. To isolate the within-country relationship between income and emissions, we use price-level-adjusted household income as an explanatory variable. We then regress the households' carbon footprint on this income measure and use country fixed effects to control for cross-country differences in the average level of household GHG emissions. Specifically, we estimate

$$F_{i,c} = \beta_1 \cdot \text{income}_{i,c} + \beta_2 \cdot \left[\frac{\text{income}_{i,c}}{1000}\right]^2 + \beta_3 \cdot \left[\frac{\text{income}_{i,c}}{1000}\right]^3 + \kappa_c + \epsilon_{i,c},$$

where i denotes an individual, c denotes a country, κ_c represents country fixed effects, and $\epsilon_{i,c}$ is the regression residual.

Table 5 reveals two key insights. First, the within-country relationship between income and emissions is non-linear. Both the second- and third-order terms are highly statistically significant, and including these terms increases the explanatory

power of the regression, as measured by the R^2 value. Second, similar to the patterns observed across countries, income is not a strong predictor of household carbon emissions. To support this statement, we isolate the share of the total variation that is exclusively explained by income (and potentially higher-order income terms) in our regression in the row "R^2 expl. by income".[20] While higher income is associated with higher carbon emissions – each additional 1000 Euros of income leads to approximately 320 kg higher household emissions – the variation explained solely by income in the regression remains below 31%, even when non-linear terms are included.

Table 5: The cross-sectional relation between income and GHG emissions

	(1)	(2)	(3)
Income in €	0.322***	0.436***	0.553***
	(0.00635)	(0.0115)	(0.0169)
(Income in 1000€)^2		−0.785***	−2.068***
		(0.1000)	(0.203)
(Income in 1000€)^3			1.786***
			(0.342)
Country FE	yes	yes	yes
N	254,147	254,147	254,147
R^2	0.415	0.448	0.463
R^2 expl. by income	0.274	0.300	0.308

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample, as no income data is available. The measure of income is price-level adjusted total household monetary net income. Robust standard errors are reported in parentheses.

The picture changes significantly when household consumption is used as an explanatory variable, as shown in Table 6. The relationship between consumption and emissions is quantitatively much stronger. Each 1000 Euros increase in consumption expenditure results in approximately 670 kg of additional carbon emissions. Furthermore, while the non-linear terms are statistically significant, they do not increase the explanatory power of the regression model. This suggests that, although the relationship between consumption and emissions may be somewhat non-linear, it is generally well approximated by a linear relationship. Lastly, even after accounting for consumption expenditure, substantial variation in GHG emissions across households remains. Overall, consumption expenditure can explain just under 64 percent of the variation in carbon footprints between households, after country fixed effects have been accounted for. The remaining 36 percent is attributed to differences in households' consumption baskets.

[20]The rest of the variation explained by the regression is due to the country fixed effects.

Table 6: The cross-sectional relation between consumption and GHG emissions

	(1)	(2)	(3)
Consumption in €	0.672***	0.766***	0.845***
	(0.00292)	(0.00598)	(0.0185)
(Consumption in 1000€)^2		−1.178***	−3.010***
		(0.0913)	(0.486)
(Consumption in 1000€)^3			10.780**
			(3.239)
Country FE	yes	yes	yes
N	254,147	254,147	254,147
R^2	0.773	0.775	0.776
R^2 expl. by consumption	0.634	0.635	0.635

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample for consistency with Table 5. The measure of consumption is price-level adjusted total household consumption. Robust standard errors are reported in parentheses.

The results derived from the regressions in Tables 5 and 6 contrast sharply with the findings from the previous section. In the cross-section of countries, we observed that even after accounting for levels or inequality of income and consumption, substantial variation in household carbon footprints across countries remained. This suggests that consumption baskets play a significant role in explaining cross-country variation in household GHG emissions. When examining within-country inequality, income remains a poor predictor of emissions, but the role of consumption in explaining emissions is much stronger. In fact, a household's total consumption explains about 64 percent of the variation in households' carbon footprints, while 36 percent is explained by the composition of the consumption basket.

Figure 8 illustrates these results. To construct this figure, we proceed as follows: We divide all sample households into percentile groups p according to their price-level-adjusted net household income. We then run regressions of the following form:

$$y_{i,p,c} = \alpha_p + \kappa_c + \varepsilon_{i,p,c}, \tag{4}$$

where y is a variable of interest for household i in income percentile p and country c. α_p denotes percentile fixed effects, κ_c denotes country fixed effects, and $\varepsilon_{i,p,c}$ is the regression residual. As explanatory variables, we use either total household consumption, total household GHG emissions, or the individual components of these emissions. This approach provides insight into the cross-sectional within-country relationship between income, consumption, and emissions. All results are smoothed using local polynomial regressions. The unsmoothed data is shown in

Figure D.3 in Appendix D.

The dashed line in Panel (a) of Figure 8 represents the 45-degree line. If household income and consumption were equal, consumption would closely follow this dashed line. However, the opposite is true. Household total consumption (measured in 1000 Euros, orange line) is higher than income at low income levels and increases along the income distribution with a slope much smaller than one. Consequently, the discrepancy between income and consumption widens as household income rises. This finding is not surprising. It is rather consistent with a world where individuals consume and save, using savings to smooth consumption over time. Household carbon emissions (measured in tons of CO2-equivalent emissions) follow a pattern similar to consumption, which aligns with the regression results presented in Table 6.

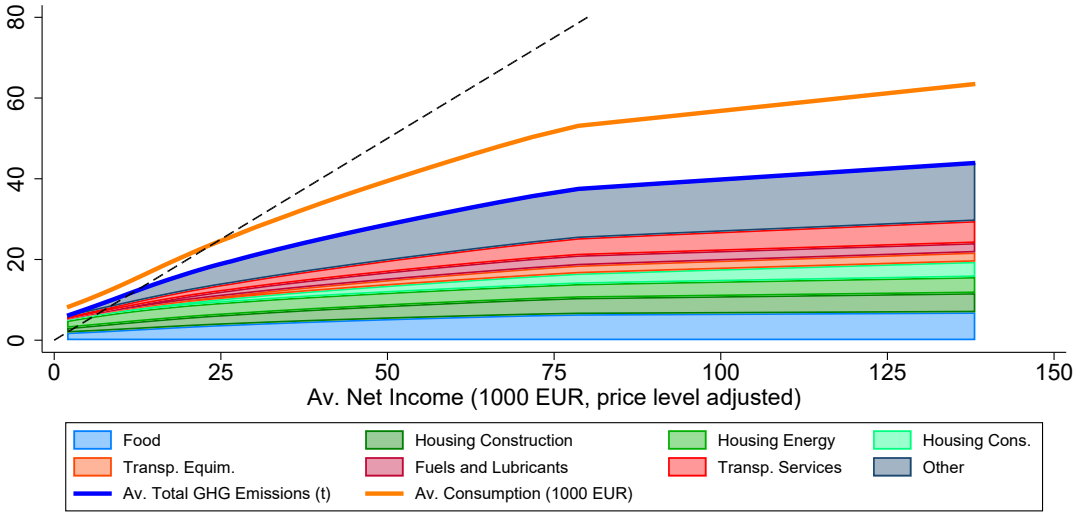
Panel (b) of Figure 8 sheds light on the relationship between consumption levels, consumption baskets, and emissions. To achieve this, we normalized all lines in Panel (a) by the level of household expenditure. The resulting lines in Panel (b) show household GHG emissions (in kg) per Euro of household spending. There are two key points to note. First, households at the lower end of the income distribution generate slightly higher emissions per Euro spent compared to households at the upper end. The emissions intensity of consumption declines along the income distribution from around 0.8 kg per Euro spent to 0.7 kg. This is a relatively small difference, consistent with the idea that consumption baskets play less of a role in explaining within-country variation in carbon footprints as compared to cross-country variation. Second, and perhaps more importantly, the composition of the consumption basket changes significantly along the income distribution. Emissions from households at the lower end of the distribution are largely related to the consumption of food, real estate, and housing energy. Together, these components account for 0.6 out of the 0.8 kg of emission intensity for these households. In contrast, transport and the consumption of other goods and services play a much smaller role for these households. For households with higher incomes, the emission intensity of food, real estate, and housing energy falls to about 0.3 kg, but these households derive much higher emissions from the consumption of transportation and other goods and services. As a result, the overall emissions intensity only declines from 0.8 to 0.7 kg per Euro spent.

The results in Figure 8 and Table 6 revealed that with respect to the household carbon footprint, accounting for household consumption is much more important than accounting for income. Still, even after controlling for the household's consumption level, a considerable amount of variation in footprints across households is left. Figure 9 shows the importance of this variation for different percentiles of the consumption distribution. To calculate this figure, we use the same regression specification as in (4), but with percentiles of the consumption distribution instead of the income distribution. The figure shows coefficients of variation of the regression residual for each consumption percentile.

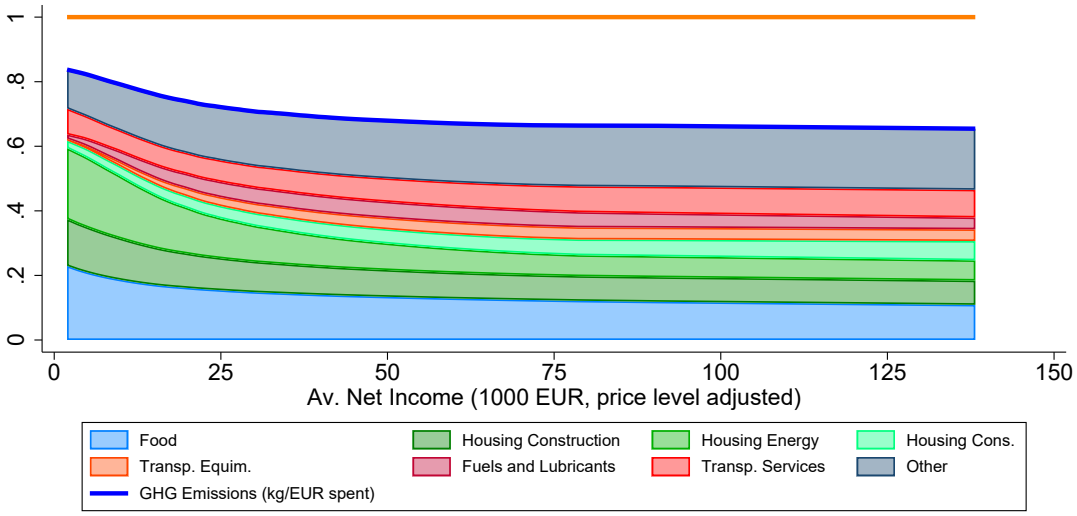
For all consumption percentiles above the 20th percentile, the coefficient of vari-

Figure 8: The within-country relation between income, consumption, and emissions

(a) Absolute



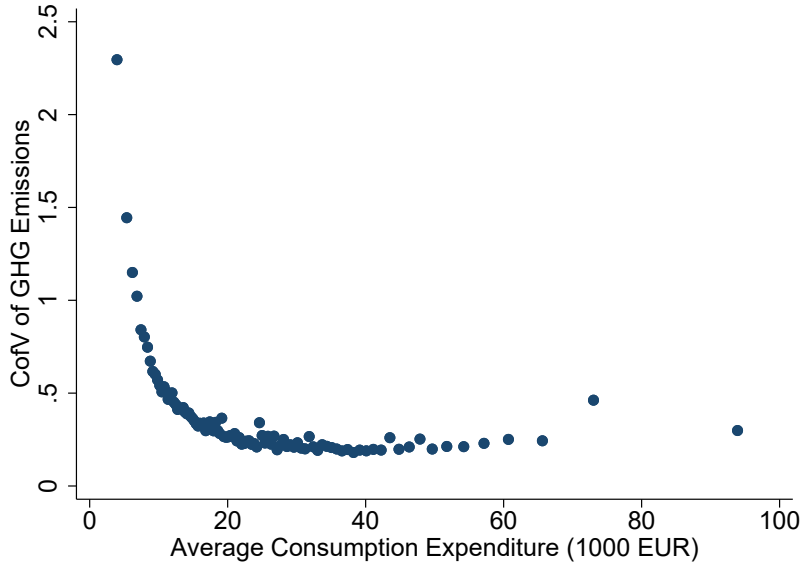
(b) Relative (per Euro spent)



Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample, as no income data is available. The measure of income is price-level adjusted total household monetary net income. The measure of consumption is price-level adjusted total household consumption. Figure shows percentile fixed-effect of regression (4) on the y-axis. The x-axis shows average income in each percentile. The fixed-effects were smoothed using local polynomial regressions. The unsmoothed data is shown in Figure D.3 in Appendix D.

ation consistently ranges from 0.25 to 0.3. This indicates that a one standard-deviation increase from the mean results in a 25% higher carbon footprint. In the lower quintile of the consumption distribution, the coefficient of variation increases significantly, reaching levels of 1.5 or even 2. This means that heterogeneity in consumption baskets plays a much larger role for this segment of the population

Figure 9: Variation in footprints for each consumption percentile



Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample for consistency with the previous analysis. The measure of consumption is price-level adjusted total household consumption. The figure shows the coefficient of variation in carbon footprints for each consumption percentile after controlling for country fixed effects.

compared to the upper four quintiles of the consumption distribution.

A final question to consider is whether, and to what extent, heterogeneity in consumption baskets can be predicted by other household observables such as age, education, or location. To investigate this, we augment regression (1) in Table 6 with additional control variables. Specifically, we control for 5-year household age bins, household size, education levels, labor market activity status, homeownership, and regional population density. The results are shown in Table 7. Details on the definition of individual variables, as well as point estimates, can be found in Appendix D. The baseline regression, which uses only consumption as an explanatory variable for household carbon emissions and accounts for country fixed effects, is repeated in column (1).[21] In regression (2), we include additional controls. Accounting for these controls does not change the regression coefficient on consumption, nor does it alter the explanatory power of the regression. Consequently, household heterogeneity in consumption baskets cannot be predicted by household characteristics. This implies that residual inequality in household GHG emissions likely stems from sources other than age, size, education, or location of households.

To sum up, we showed that, similar to the cross-country setting, income is not a strong predictor of household carbon emissions within a country. However, the

[21]Note that the number of observations in this regression is slightly lower than before, as background characteristics are not available for some households.

Table 7: Controlling for background characteristics

	(1)	(2)
Consumption in €	0.676***	0.653***
	(0.000833)	(0.00107)
Additional controls:		
5-year age groups		yes
Household size		yes
Education		yes
Labor market activity		yes
Homeownership		yes
Regional population density		yes
Country FE	yes	yes
N	241,516	241,516
R^2	0.772	0.775

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample for consistency with prior calculations. The measure of consumption is price-level adjusted total household consumption. Robust standard errors are reported in parentheses.

reasons behind this differ. In the cross-country setting, both country averages and inequality measures of income and consumption only weakly relate to averages and inequality of household GHG emissions. This suggests that across countries, the emissions intensities of different consumption items and the consumption basket play an important role in shaping a household's carbon footprint. In the within-country cross-section of households, however, consumption is a better predictor of household GHG emissions. A simple linear regression of GHG emissions on price-level-adjusted total household consumption explains around 63 percent of the variation in greenhouse gas emissions after controlling for country fixed effects. The reason why income is a poor predictor of the household carbon footprint within countries lies significantly in the consumption-income relationship, meaning that consumption is a non-linear function of income.

Yet, after accounting for the effects of total household consumption on the household carbon footprint, there is still a considerable amount of variation left, around 37 percent of the total variation in emissions across households. This variation arises from both systematic variation of household consumption baskets along the income distribution and unsystematic variation of consumption behavior within income percentiles. Systematic variation comes from the fact that poorer households have relatively higher consumption of food, real estate, and housing energy. While these households consume less transportation and other goods and services, they still exhibit a somewhat higher emissions intensity per Euro spent. Unsystematic inequality within consumption percentiles is still large. The coefficient of variation is around 0.25 to 0.30 for most consumption percentiles. At the bottom

end of the distribution, it can even increase to values of 1.5 to 2.

6 Conclusion

Inequality in household carbon footprints across households in the EU is significant. In this paper, we explore the sources of this inequality and document several important findings:

1. A substantial portion of the variation in greenhouse gas emissions across countries and households can be attributed to the consumption of food, real estate (including housing energy), and transportation.
2. Within-country inequality in GHG emissions is much larger than between-country inequality. Interestingly, carbon footprints differ from income and consumption in that a high average level of household emissions in a country tends to be associated with low inequality, and vice versa.
3. Income, in general, is a poor predictor of household carbon emissions, both across and within countries.
4. Cross-country variation is primarily due to differences in consumption baskets and potentially different emission intensities of certain consumption components.
5. Within countries, total household consumption plays a more significant role in explaining household GHG emissions. However, due to the highly non-linear income-consumption relationship, income does not.
6. Even after accounting for household consumption, approximately 37 percent of the variation in carbon footprints across households remains unexplained.

Our results have significant implications for the design of models of household GHG emissions. First, for those interested in the cross-section of countries in the EU, a suitable model must address the emissions intensities of different consumption components as well as varying consumption baskets. These factors are often influenced by a country's geographical characteristics, such as the availability of natural resources or renewable energies, and historical and cultural differences, such as the emergence of certain technologies or habits developed over time.

For those focused on within-country inequality, a primary task for modelers is to develop a suitable model of the income-consumption relationship. By providing an appropriate model of the determinants of consumption, one can explain approximately 63 percent of household carbon footprints. This suggests that static models, where net income and consumption typically coincide, are not very effective in delivering accurate outcomes. Dynamic model of the consumption-income relationship, instead, can help explain lifetime household footprints. For instance, if wealthy households do not consume, they will save resources for later (or for future generations). An interesting aspect to consider is the carbon emissions that these savings will cause in the future.

Regarding carbon pricing, an important implication of our findings relates to the

extent to which carbon pricing is implemented. We demonstrated that the importance of emissions related to certain consumption components varies along the income distribution. Households with lower net earnings tend to generate more emissions from food and housing energy, while for wealthier households, transportation and the consumption of other goods and services play a more significant role. If all carbon emissions are priced universally, the GHG emissions intensities per euro spent do not vary a lot between poor and rich households. While at the bottom of the net-earnings distribution, each euro spent causes around 0.8 kg of GHG emissions, this number declines to 0.7 kg for income richer households. However, the scenario would look quite different if only carbon emissions related to certain consumption components (e.g., food and household energy) were subject to carbon pricing.

Declaration of use of generative artificial intelligence

The authors declare that they have used generative artificial intelligence (AI), specifically (Microsoft Copilot, Writefull), to improve the language and to ensure grammatical correctness of this manuscript. No original content (including figures, or tables) was automatically generated with the help of AI. After using any AI services, the authors reviewed and edited the content of the manuscript as needed and they take full responsibility for the content of the publication.

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Online Appendix

Carbon Inequality in the EU

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March 16, 2025

A Details on data and matching procedures

Table A.1: Region overview

Regions included in databases:			Are regions included in matching procedure:
EXIOBASE 3	HBS 2015	Abbreviation:	
Austria	Austria	AT	yes
Belgium	Belgium	BE	yes
Bulgaria	Bulgaria	BG	yes
Cyprus	Cyprus	CY	yes
Czech Republic	Czechia	CZ	yes
Germany	Germany	DE	yes*
Denmark	Denmark	DK	yes
Estonia	Estonia	EE	yes
Spain	Spain	ES	yes
Finland	Finland	FI	yes
France	France	FR	yes
Greece	Greece	GR / (EL)	yes
Croatia	Croatia	HR	yes
Hungary	Hungary	HU	yes
Ireland	Ireland	IE	yes
Italy	Italy	IT	yes**
Lithuania	Lithuania	LT	yes
Luxembourg	Luxembourg	LU	yes
Latvia	Latvia	LV	yes
Malta	Malta	MT	yes
Netherlands	Netherlands	NL	yes
Poland	Poland	PL	yes
Portugal	Portugal	PT	yes
Romania	Romania	RO	yes
Sweden	Sweden	SE	yes
Slovenia	Slovenia	SI	yes
Slovakia	Slovakia	SK	yes
United Kingdom	United Kingdom	GB	no
United States	—	US	no
Japan	—	JP	no
China	—	CN	no
Canada	—	CA	no
South Korea	—	KR	no
Brazil	—	BR	no
India	—	IN	no
Mexico	—	MX	no
Russia	—	RU	no
Australia	—	AU	no
Switzerland	—	CH	no
Turkey	Turkey	TR	no
Taiwan	—	TW	no
Norway	Norway	NO	no
Indonesia	—	ID	no
South Africa	—	ZA	no
RoW Asia and Pacific	—	WA	no
RoW America	—	WL	no
RoW Europe	—	WE	no
RoW Africa	—	WF	no
RoW Middle East	—	WM	no
—	Montenegro	ME	no
—	Serbia	RS	no
—	Kosovo	XK	no

*: For Germany it was necessary to impute data from the EVS, due to a lack of expenditure data in the HBS. The procedure is described in more detail in section 2.4.2.

**: Italy is included in the main analysis, but not in the parts that focus on income, due to a lack of income data in the HBS.

Table A.2: Observation overview

Country	Original dataset	Adjusted	Dropped, due to:			Final dataset
			Neg. exp.	Zero subcat. exp.	Bottom/ Top 1%	
AT	7162	—	—	—	142	7020
BE	6135	—	—	—	122	6013
BG	2966	—	—	—	58	2908
CY	2876	674	—	3	54	2819
CZ	2929	—	22	—	58	2849
DE	50405	50404*	67	—	1002	49336
DK	2205	—	104	—	42	2059
EE	3395	932	69	156	60	3110
ES	22130	1139	—	35	440	21655
FI	3673	—	1	—	72	3600
FR	16,978	1183	59	338	330	16251
GR	6150	284	—	—	122	6028
HR	2029	—	—	—	40	1989
HU	7185	—	—	—	142	7043
IE	6839	—	—	—	136	6703
IT	15013	—	—	—	300	14713
LT	3443	53	4	20	68	3351
LU	3167	—	—	—	62	3105
LV	3844	101	8	—	76	3760
MT	3691	—	—	—	72	3619
NL	14408	—	678	—	274	13456
PL	37148	4346	—	39	742	36367
PT	11398	—	—	—	226	11172
RO	30625	—	—	—	612	30013
SE	2871	1002	134	11	48	2678
SI	3750	—	—	—	74	3676
SK	4785	—	—	—	94	4691
EU27	277200	60119	1146	602	5468	269984

Explanations: The number of observations initially included in the HBS 2015 (pre-adjustment) as well as the number of observations adjusted, dropped, and included in the final dataset. In the case of Germany, it was necessary to adjust the data differently due to a general lack of expenditure data in the HBS for the categories food, housing energy, and transportation services. The procedure is described in section 2.4.2.

B Appendix: Exploratory analysis of greenhouse gas emissions

B.1 Additional figures and tables

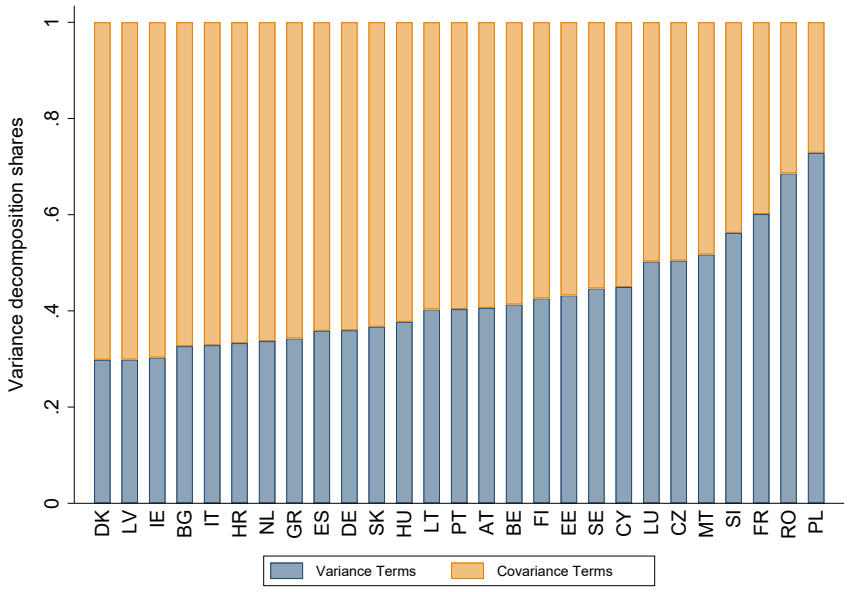
Table B.3: Average greenhouse gas emissions per consumption component

Component	**GHG emissions (kg)**	**Indirect (kg)**	**Direct (kg)**
Food	3,833	3,357	477
Housing Construction	2,347	1,560	787
Housing Energy	2,793	2,655	138
Housing Cons.	976	814	162
Transp. Equim.	749	552	197
Fuels and Lubricants	1,219	1,133	86
Transp. Services	1,670	1,472	199
Restaurants/Hotels	939	613	326
Nondur. Cons.	1,750	1,399	351
Health	244	149	95
Education	92	41	51
Fin. Services	453	263	190
Other Goods and Services	792	484	308
Total	17,859	14,493	3,367

Table B.4: Average and total (direct + indirect) carbon footprint in EU countries

	Average Footprint (in kg)		
Country	p. Household	p. Capita	Total Footprint (in kt)
RO	10,009	4,448	73,066
HR	11,212	4,287	16,185
HU	11,577	5,815	46,644
BG	11,903	5,541	34,257
LV	13,169	5,930	10,667
PT	14,096	6,099	56,865
ES	14,226	6,387	255,642
FR	14,275	7,176	403,453
SK	15,368	5,900	27,927
SE	15,757	8,187	53,811
IT	17,295	8,528	437,654
LT	17,716	9,138	23,160
NL	19,063	10,000	135,529
CZ	19,302	9,907	86,697
SI	19,437	8,640	14,841
AT	19,759	10,420	73,567
BE	19,862	9,841	93,987
DK	21,009	11,060	51,899
DE	21,529	11,574	759,984
FI	21,636	11,591	56,563
PL	21,771	9,801	289,073
MT	22,148	9,081	3,572
EE	25,211	12,512	12,740
IE	30,031	12,383	50,142
GR	31,229	13,987	125,968
CY	35,181	14,966	10,140
LU	43,266	20,947	9,433
Total	17,859	8,832	3,213,465

Figure B.1: Variance versus covariance terms

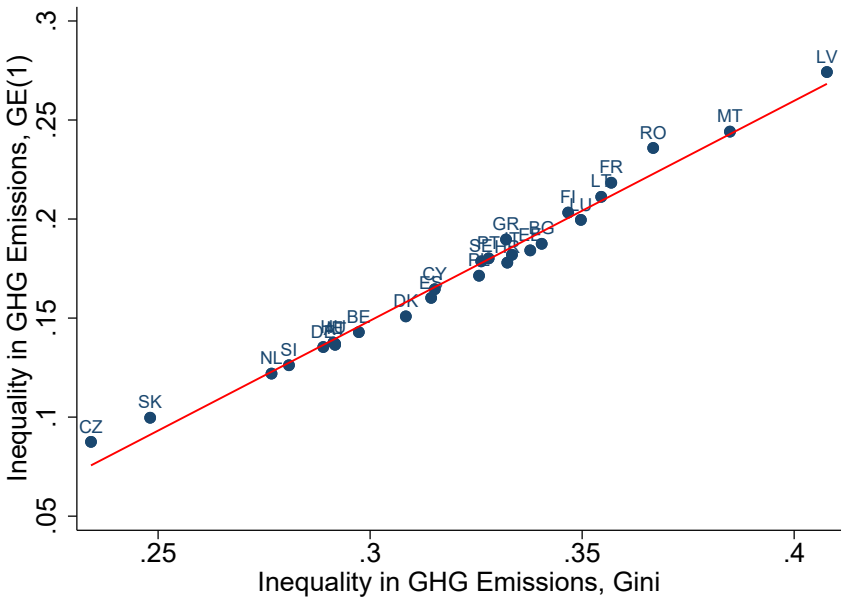


Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015.

B.2 Details of the principle component analysis

C Appendix: Emissions inequality between and within countries

Figure C.2: Gini vs. $GE(1)$ index of the household carbon footprint



Estimated slope: 1.12, R^2: 0.98

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Figure sows the relation between the Gini and the GE(1) index of inequality of household GHG emissions for each sample country.

Table C.5: Average net income and net income inequality

		Inequality $GE(1)$			
		low		high	
Average HH footprint	low	Slovakia	Bulgaria	Hungary	Croatia
			Italy		Latvia
			Romania		Lithuania
		Czech Republic			Portugal
		Poland			Estonia
					Greece
	high	Slovenia	Sweden		France
		Spain		Cyprus	Finland
		Austria	Luxembourg	Denmark	Malta
		Belgium		Ireland	
		Germany		Netherlands	

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

Table C.6: Average consumption and consumption inequality

Average HH footprint	Inequality $GE(1)$: low		Inequality $GE(1)$: high	
low	Hungary Slovakia Slovenia	Bulgaria Croatia Romania		Latvia Lithuania Portugal
	Czech Republic Poland			Estonia Greece
high		Sweden	Spain	France Italy
	Germany Denmark Ireland Netherlands		Austria Belgium Cyprus	Finland Luxembourg Malta

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

Table C.7: Average footprint and carbon inequality: Food

Average HH footprint	Inequality $GE(1)$: low		Inequality $GE(1)$: high	
low	Slovakia	Bulgaria Latvia	Hungary Spain	France Portugal
	Czech Republic Germany	Romania Malta	Austria Cyprus	
high	Slovenia	Croatia Latvia		Italy Sweden
	Denmark Poland	Greece	Belgium Ireland Netherlands	Estonia Finland Luxembourg

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

Table C.8: Average footprint and carbon inequality: Housing energy

Average HH footprint	Inequality $GE(1)$: low		Inequality $GE(1)$: high	
low	Spain	Italy	Hungary	Croatia
		Latvia		France
		Portugal		Latvia
	Belgium			Sweden
			Denmark	Luxembourg
				Malta
high	Slovakia		Slovenia	Bulgaria
	Austria	Estonia		Romania
	Czech Republic	Greece	Germany	Finland
	Cyprus		Poland	
	Ireland			
	Netherlands			

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

Table C.9: Average footprint and carbon inequality: Transportation

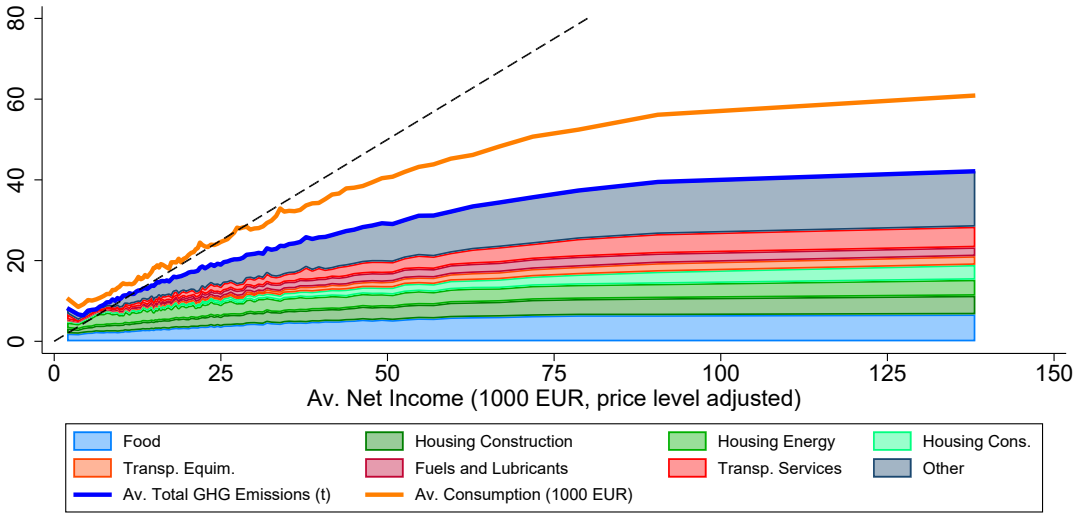
Average HH footprint	Inequality $GE(1)$: low		Inequality $GE(1)$: high	
low	Slovakia	Croatia	Hungary	Bulgaria
	Czech Republic		Spain	Portugal
	Poland			Romania
				Sweden
			Belgium	Estonia
				Finland
high	Slovenia	Italy		France
	Austria	Malta		Latvia
	Cyprus			Lithuania
	Denmark			Greece
	Germany			Luxembourg
	Ireland			
	Netherlands			

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied.

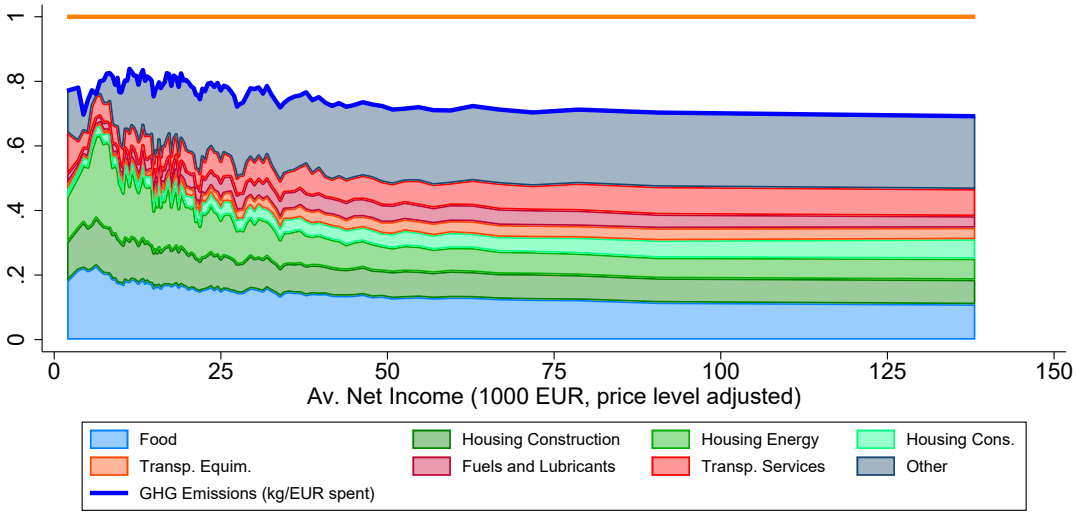
D Appendix: The income-emissions relationship

Figure D.3: The within-country relation between income, consumption, and emissions

(a) Absolute



(b) Relative (per euro spent)



Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015.

Table D.10: Regression outputs for expenditure

	(1) F_{total}	(2) F_{total}
Exp	0.669 (0.000826)	0.647 (0.00106)
$Country\ FE$		yes
Homeowner		17.534 (32.52)
$HHsize2$		653.764 (33.31)
$HHsize3$		1067.053 (45.32)
$HHsize4$		1183.612 (51.37)
$HHsize5$		1159.000 (71.62)
$HHsize6+$		1181.535 (98.53)
$Density\ interm.$		-198.335 (29.42)
$Density\ sparse$		-862.910 (31.66)
$Active1$		-167.861 (41.79)
$Active2$		-67.601 (49.73)
$Active3$		202.052 (76.76)
$Active4$		301.381 (127.9)
$Active5$		835.265 (285.6)
$Education1$		30.931 (105.0)
$Education2$		24.794 (104.9)
$Education3$		-142.361 (104.0)
$Education4$		542.569 (108.8)
$Education5$		-412.066 (112.9)
$Education6$		419.443 (108.6)
$Education7$		366.185 (111.3)
$Education9$		283.089 (114.5)
$Age5_{27}$		175.347 (87.02)
$Age5_{32}$		502.413 (83.65)
$Age5_{37}$		369.571 (83.03)
$Age5_{42}$		330.706 (82.24)
$Age5_{47}$		415.456 (81.96)
$Age5_{52}$		312.761 (81.53)
$Age5_{57}$		339.676 (81.70)
$Age5_{62}$		266.837 (82.52)
$Age5_{67}$		145.519 (85.26)
$Age5_{72}$		-28.041 (87.14)
$Age5_{77}$		-135.721 (84.37)
_cons	299.570 (72.26)	325.938 (142.6)
N	241516	241516
R^2	0.772	0.774

Explanations: Consumption expenditure has been price level adjusted using the price level conversion factors from Eurostat for ESA 2010 aggregates for 2015. Sample restricted to observations with non-missing observables. Robust standard errors are reported in parentheses.

E Product overview (later: part of Details on data)

Table E.11: Detailed overview of matching categories

Matching categories		**HBS product allocation**		**EXIOBASE product allocation**	
Code	**CatName**	**Code**	**COICOP Category /Eurostat Data 2015**	**Code**	**EXIOBASE Products**
10	**Food and Drinks**				
10.1	Food				
10.11	Cereal, grains, crops and bread				
10.111	Rice	01.111	Rice	p01.a	Paddy rice
				p15.g	Processed rice
10.112	Other cereal products	01.112	Flours and other cereals	p01.b	Wheat
		01.113	Bread	p01.c	Cereal grains nec
		01.114	Other bakery products	p01.g	Plant-based fibers
		01.115	Pizza and quiche	p01.h	Crops nec
		01.116	Pasta products and couscous		
		01.117	Breakfast cereals		
		01.118	Other cereal products		
10.12	Meat	01.12	Meat	p01.k	Poultry
				p01.l	Meat animals nec
				p15.a	Products of meat cattle
				p15.b	Products of meat pigs
				p15.c	Products of meat poultry
				p15.d	Meat products nec
10.13	Fish and seafood	01.13	Fish and seafood	p05	Fish and other fishing products; services incidental of fishing (05)
				p15.k	Fish products
10.14	Milk and dairy products	01.141	Milk, whole, fresh	p01.n	Raw milk
		01.142	Milk, low fat, fresh	p15.f	Dairy products
		01.143	Milk, preserved		
		01.144	Yoghurt		
		01.145	Cheese and curd		
		01.146	Other milk products		
10.15	Vegetable oils and fats	01.152	Margarine and other vegetable fats	p15.e	Products of vegetable oils and fats
		01.153	Olive oil		
		01.154	Other edible oils		
10.16	Vegetables, fruits and nuts	01.16	Fruit	p01.d	Vegetables, fruit, nuts
		01.17	Vegetables		
10.17	Sugar	01.181	Sugar	p15.h	Sugar
10.18	Other animal products	01.147	Eggs	p01.m	Animal products nec
		01.151	Butter		
		01.155	Other edible animal fats		
10.19	Other food products	01.182	Jams, marmalades and honey	p01.e	Oil seeds
		01.183	Chocolate	p15.i	Food products nec
		01.184	Confectionery products		
		01.185	Edible ices and ice cream		
		01.186	Artificial sugar substitutes		
		01.19	Food products n.e.c.		
		01.191	Sauces, condiments		
		01.192	Salt, spices and culinary herbs		
		01.193	Baby food		
		01.194	Ready-made meals		

Table E.11 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
		01.199	Other food products n.e.c.		
10.2	Beverages	01.2	Non-alcoholic beverages	p15.j	Beverages
		02.1	Alcoholic beverages		
10.3	Tobacco	02.2	Tobacco	p16	Tobacco products (16)
20	**Housing Construction**	04.1	Actual rentals for housing	p20	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials (20)
		04.2	Imputed rentals for housing	p26.c	Bricks, tiles and construction products, in baked clay
		04.3	Maintenance and repair of the dwelling	p26.d	Cement, lime and plaster
		04.4	Water supply and miscellaneous services relating to the dwelling	p26.e	Other non-metallic mineral products
				p27.5	Foundry work services
				p27.a	Basic iron and steel and of ferro-alloys and first products thereof
				p41	Collected and purified water, distribution services of water (41)
				p45	Construction work (45)
				p70	Real estate services (70)
				p90.1.a	Food waste for treatment: incineration
				p90.1.b	Paper waste for treatment: incineration
				p90.1.c	Plastic waste for treatment: incineration
				p90.1.d	Intert/metal waste for treatment: incineration
				p90.1.e	Textiles waste for treatment: incineration
				p90.1.f	Wood waste for treatment: incineration
				p90.1.g	Oil/hazardous waste for treatment: incineration
				p90.2.a	Food waste for treatment: biogasification and land application
				p90.2.b	Paper waste for treatment: biogasification and land application
				p90.2.c	Sewage sludge for treatment: biogasification and land application
				p90.3.a	Food waste for treatment: composting and land application
				p90.3.b	Paper and wood waste for treatment: composting and land application
				p90.4.a	Food waste for treatment: waste water treatment
				p90.4.b	Other waste for treatment: waste water treatment
				p90.5.a	Food waste for treatment: landfill
				p90.5.b	Paper for treatment: landfill
				p90.5.c	Plastic waste for treatment: landfill
				p90.5.d	Inert/metal/hazardous waste for treatment: landfill

Table E.11 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
				p90.5.e	Textiles waste for treatment: landfill
				p90.5.f	Wood waste for treatment: landfill
21	**Housing Energy**				
21.1	Electricity	04.51	Electricity	p40.11.a	Electricity by coal
				p40.11.b	Electricity by gas
				p40.11.c	Electricity by nuclear
				p40.11.d	Electricity by hydro
				p40.11.e	Electricity by wind
				p40.11.f	Electricity by petroleum and other oil derivatives
				p40.11.g	Electricity by biomass and waste
				p40.11.h	Electricity by solar photovoltaic
				p40.11.j	Electricity by tide, wave, ocean
				p40.11.k	Electricity by Geothermal
				p40.11.l	Electricity nec
				p40.12	Transmission services of electricity
				p40.13	Distribution and trade services of electricity
21.2	Gas	04.52	Gas	p40.2.1	Distribution services of gaseous fuels through mains
				p40.2.a	Coke oven gas
				p40.2.b	Blast furnace gas
				p40.2.d	Gas works gas
				p40.2.e	Biogas
21.3	Liquid fuels	04.53	Liquid fuels	p11.a	Crude petroleum and services related to crude oil extraction, excluding surveying
				p23.20.e	Kerosene
				p23.20.f	Gas/diesel oil[a]
21.4	Solid fuels	04.54	Solid fuels	p10.a	Anthracite
				p10.b	Coking Coal
				p10.c	Other bituminous coal
				p10.d	Sub-bituminous coal
				p10.e	Patent fuel
				p10.f	Lignite/brown coal
				p10.g	BKB/peat briquettes
				p10.h	Peat
				p23.1.a	Coke oven coke
				p23.20.q	Petroleum coke
				p24.e	Charcoal
21.5	Heat energy	04.55	Heat energy	p40.3	Steam and hot water supply services
22	**Housing Consumption**	05	Furnishings, household equipment and routine household maintenance	p17	Textiles (17)
				p26.b	Ceramic goods
				p27.45	Other non-ferrous metal products
				p28	Fabricated metal products, except machinery and equipment (28)
				p29	Machinery and equipment n.e.c. (29)
				p30	Office machinery and computers (30)
				p31	Electrical machinery and apparatus n.e.c. (31)
				p36	Furniture; other manufactured goods n.e.c. (36)
				p95	Private households with employed persons (95)

Table E.11 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
				p25	Rubber and plastic products (25)[c]
30	**Purchase and maintenance of vehicles**	07.1	Purchase of vehicles	p25	Rubber and plastic products (25)[c]
		07.21	Spare parts and accessories for personal transport equipment	p34	Motor vehicles, trailers and semi-trailers (34)
		07.23	Maintenance and repair of personal transport equipment	p35	Other transport equipment (35)
		07.24	Other services in respect of personal transport equipment	p50.a	Sale, maintenance, repair of motor vehicles, motor vehicles parts, motorcycles, motor cycles parts and accessoiries
				p71	Renting services of machinery and equipment without operator and of personal and household goods (71)
31	**Fuels and lubricants**			p50.b	Retail trade services of motor fuel[b]
31.1	Diesel	07.221	Diesel	p23.20.f	Gas/diesel oil[a]
				p24.h	Biodiesels
31.2	Petrol	07.222	Petrol	p23.20.a	Motor gasoline
				p23.20.b	Aviation gasoline
				p23.20.c	Gasoline type jet fuel
				p24.g	Biogasoline
31.3	Other fuels and lubricants	07.223	Other fuels for personal transport equipment	p23.20.d	Kerosene type jet fuel
		07.224	Lubricants	p23.20.g	Heavy fuel oil
				p23.20.i	Liquefied petroleum gases (LPG)
				p24.i	Other liquid biofuels
32	**Transportation services**				
32.1	Railway transportation services	07.31	Passenger transport by railway	p60.1	Railway transportation services
32.2	Air transportation services	07.33	Passenger transport by air	p62	Air transport services (62)
32.3	Sea and inland waterway transportation services	07.34	Passenger transport by sea and inland waterway	p61.1	Sea and coastal water transportation services
				p61.2	Inland water transportation services
32.4	Other transportation services	07.32	Passenger transport by road	p60.2	Other land transportation services
		07.35	Combined passenger transport	p60.3	Transportation services via pipelines
		07.36	Other purchased transport services		
40	**Hotels and Restaurants**	11	Restaurants and hotels	p55	Hotel and restaurant services (55)
50	**Nondurable Consumption**	02.3	Narcotics	p02	Products of forestry, logging and related services (02)
		03	Clothing and footwear	p14.3	Chemical and fertilizer minerals, salt and other mining and quarrying products n.e.c.
		09	Recreation and culture	p18	Wearing apparel; furs (18)
		12.1	Personal care	p19	Leather and leather products (19)
				p21.2	Paper and paper products
				p22	Printed matter and recorded media (22)
				p24.b	N-fertiliser
				p24.c	P- and other fertiliser
				p24.d	Chemicals nec
				p24.f	Additives/blending components

Table E.11 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
				p27.41	Precious metals
				p27.42	Aluminium and aluminium products
				p32	Radio, television and communication equipment and apparatus (32)
				p33	Medical, precision and optical instruments, watches and clocks (33)
				p37	Secondary raw materials
				p63	Supporting and auxiliary transport services; travel agency services (63)
				p72	Computer and related services (72)
				p91	Membership organisation services n.e.c. (91)
				p92	Recreational, cultural and sporting services (92)
60	**Health**	06	Health	p85	Health and social work services (85)
70	**Education**	10	Education	p80	Education services (80)
80	**Finance**	12.5	Insurance	p65	Financial intermediation services, except insurance and pension funding services (65)
		12.6	Financial services n.e.c.	p66	Insurance and pension funding services, except compulsory social security services (66)
				p67	Services auxiliary to financial intermediation (67)
90	**Other Goods and Services**	08	Communications	p51	Wholesale trade and commission trade services, except of motor vehicles and motorcycles (51)
		12.2	Prostitution; other services n.e.c.	p52	Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods (52)
		12.3	Personal effects n.e.c.	p64	Post and telecommunication services (64)
		12.4	Social protection	p73	Research and development services (73)
				p74	Other business services (74)
				p75	Public administration and defence services; compulsory social security services (75)
				p93	Other services (93)

Explanations:
[a]: Emissions corresponding to the final demand of the EXIOBASE product classification ¨Gas/Diesel Oil¨ were distributed among the household energy subcategory ¨Liquid Fuels¨ (21.3) and the transportation subcategory ¨Diesel¨ (31.1), as this product is typically used for both purposes. This was done using the gas oil and diesel consumption ratios generated from the HBS data. For this we made the assumption that the price ration of diesel over gas oil is $1,6$.
[b]: Emissions corresponding to the final demand of the EXIOBASE product classification ¨Retail trade services of motor fuel¨ were distributed among the three subcategories ¨Diesel¨, ¨Petrol¨ and ¨Other Fuels and lubricants¨ (31.1-31.3) according to their respective proportion of the total emissions of the ¨Fuels and Lubricants¨ category (31).
[c]: Emissions corresponding to the final demand "Rubber and plastic products (25)" were distributed among the category "Housing Consumption" (22) and the transportation subcategory "Purchase and maintenance of vehicles" (30), where rubber products are also used in the form of tires for vehicles.