From Annual Income to Lifetime Emissions: A Lifecycle Theory of Carbon Inequality

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Abstract

We study inequality in household carbon footprints in 26 countries of the EU. Using a novel harmonized dataset that combines environmentally extended supply-use tables with the European Household Budget Survey, we document substantial heterogeneity in household level carbon emissions, driven primarily by within-country differences. Most importantly, we find that net income is only a weak predictor of household carbon footprints.

To interpret this finding, we develop and calibrate an overlapping generations model with non-homothetic CES preferences. The model is disciplined by three key forces shaping emissions inequality: a non-proportional consumption-income relationship, heterogeneity in consumption baskets, and variation in emissions intensities across goods. It matches the joint distribution of income, consumption, and emissions and provides a framework to evaluate the distributional and welfare effects of carbon pricing. We then use the model to show that lifetime earnings are closely aligned with lifetime carbon footprints.

JEL Classification: Q52, D15, D31, E21
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1 Introduction

Pricing greenhouse gas emissions is an essential tool in environmental policy. Following the Pigouvian principle (Pigou, 1920), carbon pricing internalizes the social cost of emissions and provides incentives for mitigation (Nordhaus, 2017). At the same time, 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.

Understanding the distributional effects of carbon pricing requires a precise understanding of how greenhouse gas emissions are distributed across households. Since a large share of emissions is ultimately linked to private consumption (Ivanova et al., 2017), the cross-sectional distribution of household carbon footprints is a key object of interest. However, comprehensive and harmonized evidence on household-level emissions across the European Union remains limited.

In this paper, we analyze the distribution of household-level carbon footprints across the 27 member 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 2015 European 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. The consumption expenditure data is categorized based on the 5-

[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.

Digit COICOP classification.[2] EXIOBASE traces the production processes of 200 different product groups throughout their entire supply chains, from origin to destination. Further, it includes environmental extensions that record emissions to air for 27 different pollutants, both from combustion and non-combustion sources. We translate these product groups into COICOP consumption categories and allocate the associated emissions to households based on their observed expenditures. This procedure yields a micro dataset covering more than 270,000 households across the EU, containing detailed consumption expenditure and corresponding total carbon footprint of each household. This comprehensive dataset enables us to explore the dimensions of both between- and within-country inequality in household carbon footprints within the EU.

We derive a series of stylized facts on the cross-sectional distribution of household-level greenhouse gas emissions. First, the majority of consumption-related emissions are indirect, arising along global supply chains. Second, there is substantial heterogeneity in average carbon footprints across EU countries. Third, within-country variation in households' carbon footprints is an order of magnitude greater than cross-country variation. A formal decomposition using generalized entropy indices reveals that around 85 percent of EU-wide carbon inequality is driven by within-country dispersion. However, this decomposition differs across of household-level GHG emission components, with housing energy exhibiting particularly strong cross-country differences.

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.

A central finding is that income is only a weak predictor of household carbon emissions. Across countries, price-level-adjusted household net income explains only a limited fraction of average carbon footprints. Within countries, the relationship between current net income and emissions is also weak. This reflects a highly nonlinear income–consumption relationship: 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.

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

Total consumption is a much stronger predictor of emissions, explaining around 63 percent of the variation in carbon footprints. Yet a substantial residual component remains. This residual reflects both systematic differences in consumption baskets along the income distribution — for example, higher food and housing-energy shares among poorer households and higher transportation shares among richer households — and unsystematic heterogeneity in expenditure composition within consumption groups. In addition, emission intensities differ across and within consumption categories, further contributing to dispersion in carbon footprints.

These empirical findings have important implications for the design of quantitative models of the household carbon footprint. 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 replicating the observed patterns and delivering accurate outcomes. A credible framework must jointly account for nonlinear income–consumption dynamics, systematic and idiosyncratic variation in expenditure shares, and heterogeneity in emission intensities.

To address this challenge, we develop a multi-country overlapping-generations life-cycle model with heterogeneous agents and non-homothetic CES preferences. The life-cycle structure with idiosyncratic income risk generates a realistic income–consumption relationship. Non-homothetic preferences produce systematic shifts in expenditure shares along the consumption distribution. Additional taste and emission-intensity shifters capture within-group heterogeneity. The model is explicitly designed to replicate the stylized facts documented in the data.

By combining a harmonized EU-wide micro dataset with a structural heterogeneous-agent model tailored to match observed consumption and emission patterns, our paper provides a unified framework for understanding the distribution of household carbon footprints in Europe. This framework provides a foundation for subsequent analyses of carbon pricing and redistribution within and across EU member states.

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 aggre-

gate emissions data and household-level consumption data. In Section 2.4, we provide a set of stylized facts of cross-country and within-country inequality of carbon footprints. Section 2.5 provides a formal decomposition of the between- and within-country carbon inequality, and Section 3 discusses the relationship between household income and carbon emissions. Section 4 introduces a general equilibrium life-cycle model with a non-homothetic CES-aggregator that is able to replicate the relationship we see in the data. In Section 5 we discuss its calibration and in Section 6 we show simulation results. Section 7 offers some concluding remarks.

Literature review preliminary, to be completed

The economic foundation of carbon pricing rests on Pigouvian taxation (Pigou, 1920; Baumol and Oates, 1988) and welfare-based assessments of the social cost of carbon (Nordhaus, 2017). A substantial literature studies the efficiency and revenue-recycling properties of environmental taxes, including the "double dividend" hypothesis (Goulder, 1995; Bovenberg, 1999). While these contributions primarily focus on efficiency and optimal tax design, distributional concerns have increasingly become central to both policy debates and quantitative climate policy analysis.

From a household-level perspective, understanding distributional effects requires a detailed account of how income, consumption, and expenditure composition vary across households. A large body of research in household finance studies consumption dynamics under incomplete markets and idiosyncratic income risk (Deaton, 1992; Carroll, 1997; Attanasio and Weber, 1993; Attanasio, 1999). These models emphasize precautionary saving, liquidity constraints, and life-cycle motives as key drivers of nonlinearities in the income–consumption relationship and of cross-sectional dispersion in consumption outcomes.

More recent heterogeneous-agent macroeconomic frameworks extend this perspective by highlighting substantial heterogeneity in marginal propensities to consume, wealth accumulation, and expenditure shares across households (Kaplan and Violante, 2014; Kaplan et al., 2018). Empirical evidence using administrative micro data confirms large dispersion in consumption responses across households (Fagereng et al., 2021). Quantitative heterogeneous-agent models further demonstrate that such distributional features of the household sector are central for aggregate dynamics and policy transmission (Auclert et al., 2020; Violante, 2022). While this literature provides a rich framework for modeling income risk, life-cycle behavior, and cross-sectional consumption heterogeneity, it has largely abstracted from environmental externalities and from the interaction between carbon intensity and non-homothetic composition of household expenditure baskets.

Empirical research documents substantial heterogeneity in household carbon footprints. Using environmentally extended input-output tables combined with household expenditure surveys, studies such as Weber and Matthews (2008), Wier et al. (2001), Baiocchi et al. (2010), Büchs and Schnepf (2013), and Hubacek et al.

(2017) show that emissions generally increase with income, though often less than proportionally. Estimates of the income elasticity of emissions are typically below one (Chakravarty et al., 2009; Sager, 2019), and several studies document concave environmental Engel curves (Kahn, 1998; Heerink et al., 2001; Sager, 2019). Cross-country evidence highlights substantial global carbon inequality (Hubacek et al., 2017; Chancel and Piketty, 2015; Chancel, 2022). More recent work by Nielsen et al. (2024) shows that standard indicators typically underestimate the extent of carbon footprint inequality across different national settings, highlighting the need for granular, micro-level footprint data to accurately evaluate distributional outcomes.

Beyond income, emissions depend strongly on consumption composition and on the carbon intensity of goods and services. Consumption-based accounting approaches (Davis et al., 2010) emphasize the importance of indirect emissions embodied in traded goods. Household characteristics such as size, housing conditions, and location further shape carbon footprints (Druckman and Jackson, 2016; Gough et al., 2011). Yet most of this empirical literature is descriptive in nature and does not embed carbon exposure within a structural model of household behavior under risk.

At the same time, quantitative climate policy models — whether microsimulation approaches (Heindl and Löschel, 2015; Timilsina, 2018; Maier et al., 2024) or computable general equilibrium models (Jorgenson et al., 1992, 2013; McKibbin and Wilcoxen, 2013) — typically rely on stylized household structures. They are not designed to replicate the granular cross-sectional heterogeneity in income, consumption dynamics, and expenditure composition highlighted in the household finance literature, nor to capture the detailed cross-sectional variation in carbon footprints documented in micro-level data.

Our paper contributes to this literature along three dimensions. First, we construct a harmonized micro dataset of household carbon footprints for all 27 EU member states based on a consistent integration of EXIOBASE and HBS data. Second, we document novel stylized facts on the joint distribution of income, consumption, expenditure composition, and emissions across and within countries. Third, we develop a heterogeneous-agent overlapping-generations model with with idiosyncratic income risk and non-homothetic preferences that is explicitly calibrated to replicate these empirical patterns for 26 EU countries. By structurally linking life-cycle income dynamics, precautionary saving behavior, consumption composition, and emission intensities, we provide a micro-founded explanation for the substantial dispersion in household carbon footprints that cannot be accounted for by income alone.

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). The foundation of EXIOBASE is a basic input-output framework, see Leontief (1936, 1970).[3] 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[4]. 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.2 contains an overview of those regions. We use the product by product 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 G.15 and more information about the dataset is available at Stadler et al. (2018). The EXIOBASE dataset additionally reports GHG emission that are associated with the respective product category.[5] In summary, the environmentally extended supply-use tables of EXIOBASE make it possible to quantify the overall footprint associated with the consumption of 200 distinct products across 49 world regions. Moreover, they enable a breakdown into *indirect* emissions, which occur during the production process, and *direct* emissions, which arise from the final use phase in the respective region.

2.2 The European 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 demographics, 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.

[3] A more detailed overview of input-output analysis in general can be found in Miller and Blair (2009).

[4] For more information see Stadler et al. (2021).

[5] More information on the different accounts can be found in Section A.1 of the appendix or elsewhere (Stadler et al., 2018).

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.2.

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 purchasers' 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.3. 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 cruder 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. Using a similar Input-Output data set and combining it with tax information and household surveys, Chancel (2022) takes carbon inequality to the global level but he does not have disaggregated

household consumption.

The procedure to match the data from the EXIOBASE with the data from the HBS is described in detail in Section A.2 of the appendix. Table A.2 summarizes the EU27 countries that are included in our final matching procedure and following analysis. In total, we match the two datasets across 39 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 A.1 in the appendix. A detailed alignment of the HBS classification system and the EXIOBASE products to the chosen matching categories based on their predominant use (as in Büchs et al. (2021)) is summarized in Table G.15.[6] There were some additional steps necessary to successfully match the two datasets. They consist of a price transformation of the HBS expenditure from purchaser prices to basic prices, the treatment of special cases of products and countries and some data cleansing steps. Our final dataset covers 271920 households for which we were able to calculate total, direct and indirect household level GHG emission footprints across 39 matching product categories for 27 EU countries.[7] All of those procedures are described in detail in section A.2 in the appendix.

2.4 Descriptive statistics

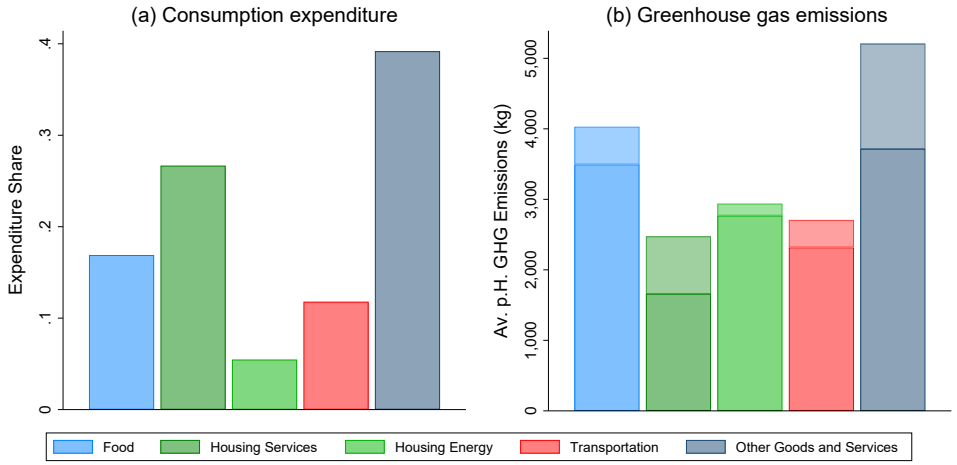
We start by documenting the key descriptive features of the distribution of greenhouse gas (GHG) emissions in our sample. Household-level emissions are linked to consumption behavior. Panel (a) of Figure 1 illustrates the expenditure share across 5 main consumption components for the pooled sample of all EU households. The three largest components of total household consumption expenditures are food, housing services (including rents), and other goods and services. The picture changes significantly when we examine the GHG emissions associated with these 5 consumption components, as shown in panel (b) of Figure 1.[8] On average, a typical EU household emits approximately 18 tons of greenhouse gases per year, measured in CO2 equivalents. Housing energy and transportation (including 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.

[6] A limiting underlying assumption of this matching is that there is no heterogeneity in footprints within one category.

[7] 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).

[8] The data behind this figure are shown in Table B.4 in Appendix B.

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



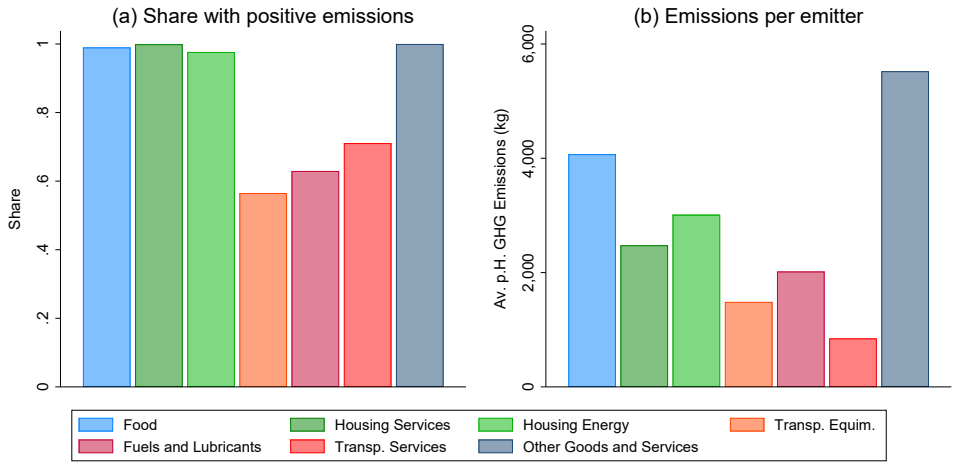
Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Panel (a): average expenditure on different consumption components relative to average total household spending. Panel (b): average per household GHG emissions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

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, emerging somewhere along the supply chain and constituting around 80% of total emissions. 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).

A key insight from Figure 1 is the pronounced difference in the magnitudes of the expenditure shares and associated emissions. Certain consumption categories, such as housing services (e.g., rent), exhibit a high share in total expenditure but are responsible for only a comparatively small share of greenhouse gas emissions. In contrast, other categories, such as housing energy, account for a relatively minor portion of total expenditure while generating a disproportionately large emission footprint. By contrast, the expenditure share and emission contribution of other goods and services appear to be closely aligned, indicating a more proportional relationship between spending and emissions in this residual category.

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 Figure 2 shows the share of EU households that generate positive GHG emissions through any of the 5 main consumption components. Unsurprisingly, almost all households have positive GHG emissions related to food, real estate, transportation services 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. 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. 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.

Figure 2: Extensive vs. intensive margin emissions



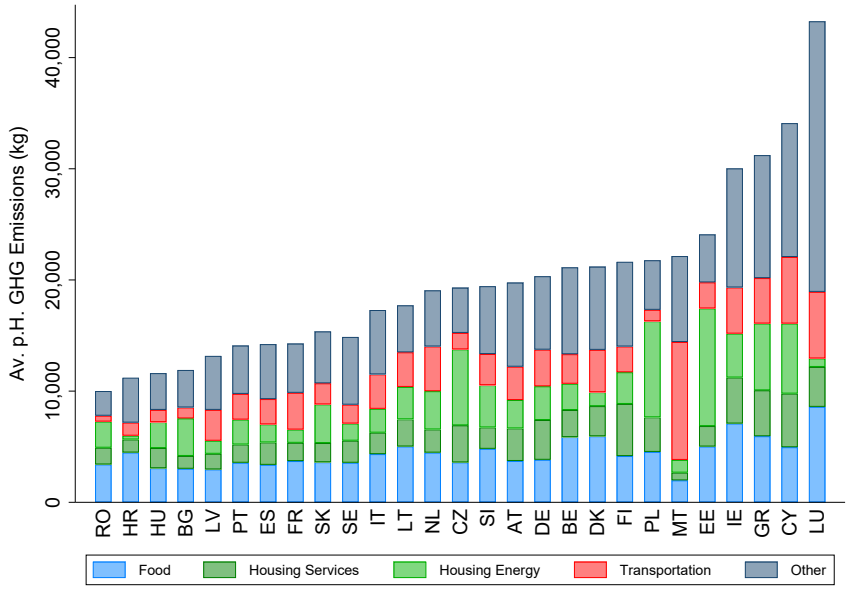
Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied in calculating statistics. Panel (a): share of households with positive GHG emissions related to the different consumption componens. Panel (b): average per household GHG emissions for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

2.4.1 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:

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 household carbon footprint for the entire EU is approximately 18 tons of CO2-equivalent emissions. The bulk of these emissions are related to the consumption of food, housing (including energy), and transportation. 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. Major cross-country variation in greenhouse gas footprints predominantly arises from differences in emissions related to housing energy and transportation.

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.

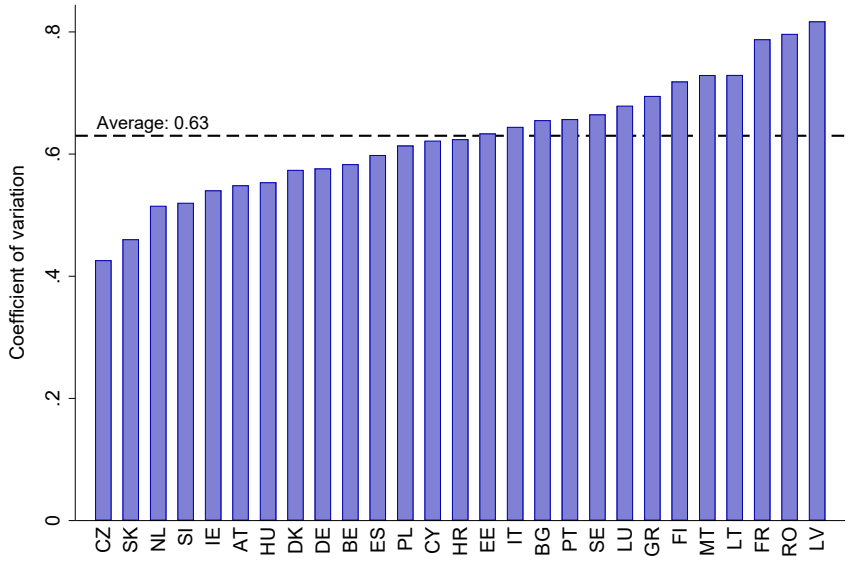
When looking at the individual components of the carbon footprint, the most significant differences in GHG emissions across countries are related to housing, particularly housing energy, and transport. The Czech Republic, Poland, and Estonia are among the highest emitters of greenhouse gases from housing 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 housing services is relatively uniform across countries. The only exception from this is

Luxembourg, where emissions related to food and the other goods and services category (incl. nondurable consumption) are extraordinarily large.

2.4.2 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.

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.

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 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 $\mathrm{Cov}(F_j, F_k)$. We refer to the sum of these terms as the variance-covariance contribution associated with component j. Importantly, this decomposition does not provide an orthogonal attribution of total variance to individual components, as covariance terms are shared across components. The reported contributions should therefore be interpreted as descriptive measures of joint variation rather than as isolated marginal effects of each consumption category.

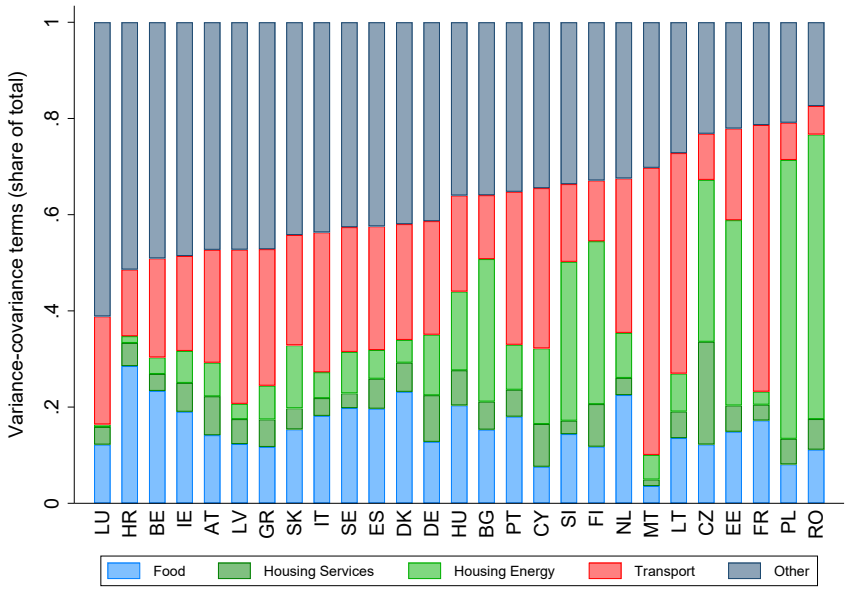
Figure 5 shows the variance-covariance contributions of household-level GHG emissions associated with the five aggregated consumption categories as a share of total variance in household carbon footprints for each country. We find that a large fraction of overall variation in household-level carbon footprints – ranging from 60% to 85% – is related to the consumption of food, real estate (including housing energy), and transportation. However, this reflects not only variation within these components themselves, but also their co-movement with other consumption categories. The relative importance of these consumption components varies across countries. For example, housing energy is strongly associated with the between-household variation in carbon emissions in Bulgaria, the Czech Republic, Estonia, Finland, Poland, and Romania, while transportation plays a more prominent role in countries such as Cyprus, France, Greece, Latvia, and Malta.

The decomposition of emissions from different consumption components in Figure 5 is incomplete, as it abstracts from the fact that covariance terms are not separately identified but instead enter the contribution of each component. In fact, when examining these covariance terms directly (see Figure B.2 in Appendix B), we find that they account for roughly 60% of total variance. This highlights that a substantial part of the variation in household carbon footprints arises from the joint variation of consumption components rather than from independent variation within individual categories. In other words, consumption patterns across goods are strongly interrelated and cannot be viewed in isolation.

2.4.3 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

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.

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 carbon 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.

2.5 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 $\mathcal{N}$.[9] Figure C.3 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

[9] Note that this index is non-negative and is not capped at 1 like the Gini index. Further, the $GE(1)$ is only equal to zero if all individual carbon footprints F_i are equal to the population average $\bar{F}$ such that we sum over $\log(1)$. This would only be the case if there is no variation in the carbon footprints of individuals in the population.

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 1. 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 around 86% of the total variation in household GHG emissions across the entire EU. It is also true for sub-components related to the consumption of food, housing services, and transportation. However, this is not as pronounced 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 about 18 percent. These results highlight the significant role of geography in shaping a country's GHG emissions. 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 3, we will investigate heterogeneity in household consumption baskets within countries more thoroughly.

Table 1: Inequality decomposition between- and within country

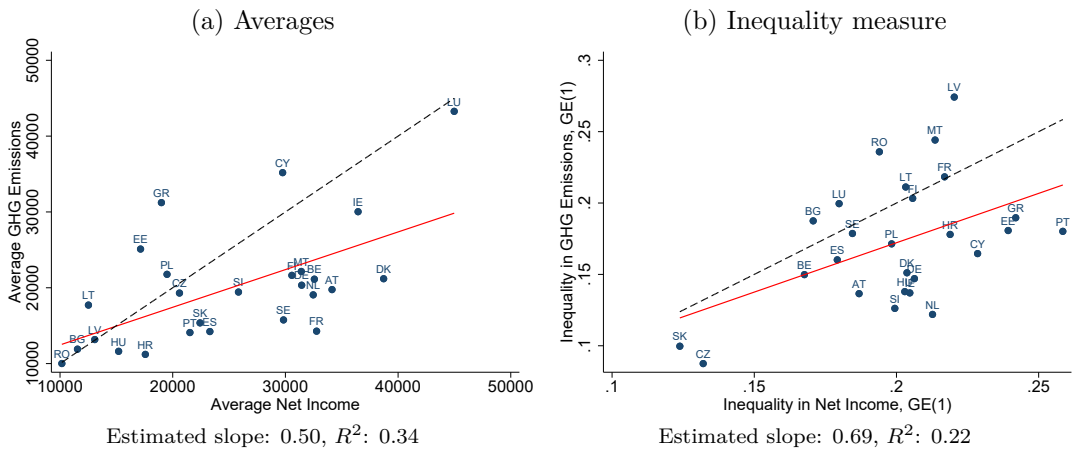
			decomposition		share
	Gini	$GE(1)$	within	between	within
Total footprint	0.343	0.196	0.168	0.028	0.858
Food	0.369	0.228	0.214	0.015	0.937
Housing Services	0.340	0.196	0.135	0.061	0.690
Housing Energy	0.522	0.531	0.337	0.194	0.635
Transportation	0.612	0.719	0.653	0.066	0.908
Net income	0.378	0.243	0.202	0.041	0.832
Consumption	0.324	0.171	0.146	0.025	0.854

Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were applied. Excluding Italy in the decomposition of net income inequality.

To shed more light on the link between income and emissions inequality, 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 posi-

tive 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.[10] However, the relationship is relatively weak, as measured by the explanatory power of the simple regressions. A linear regression can only explain 34 percent of the variance in average GHG emissions across countries and only 22 percent of the variance in inequality.[11] 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: 0.22

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.

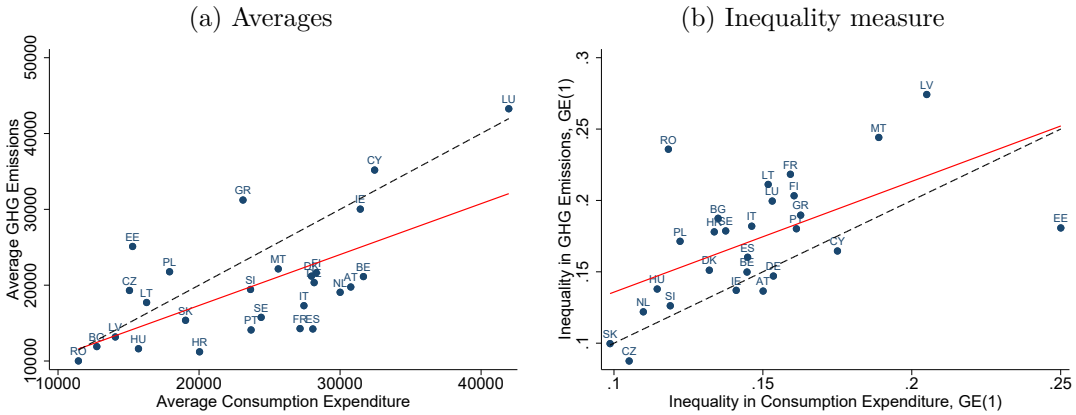
One reason for the weak relationship between household income and household carbon emissions may be that emissions are more closely associated with household consumption rather than income. In Figure 7, we repeat the same analysis but use price-level-adjusted household total consumption instead of income. 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

[10]The latter relationship is somewhat biased by the Czech Republic and Slovakia. Eliminating these two from the graph would significantly weaken the relationship between income inequality and emissions inequality, see Figure C.4 in Appendix C.

[11]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.

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 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.

3 A decomposition of the carbon footprint

The previous section focused on differences in household GHG emissions across and within countries. We saw that the majority of inequality in those emissions is due to within country effects. In this section, we investigate the household carbon footprint within countries in more detail. To analyse the households carbon footprint in a more structured way, let us propose the following decomposition. Let us denote by F_i the total carbon footprint of an individual i that consumes $g = 1, \ldots, G$ different goods. If we further assume that the income and total consumption expenditure of this individual are given by Y_i and C_i, with $C_{i,g}$ indicating the consumption expenditure for good g, then we can write

$$F_i = \sum_{g=1}^{G} F_{i,g} = \sum_{g=1}^{G} \underbrace{Y_i}_{\text{income}} \times \underbrace{\frac{C_i}{Y_i}}_{\text{cons.-inc. relationship}} \times \underbrace{\frac{C_{i,g}}{C_i}}_{\text{cons. basket}} \times \underbrace{\frac{F_{i,g}}{C_{i,g}}}_{\text{emission int.}} . \quad (1)$$

This simple decomposition of the carbon footprint suggests that carbon emissions on the household level are due to three single elements: the consumption-income relationship, the composition of the consumption basket given a certain level of consumption and the emission intensity of different items of the consumption basket. In the following sections, we will analyze each of those components separately. We will concentrate on the goods that we saw were the main contributors to the GHG emissions of households: Food, Housing Services, Housing Energy and Transport. All other goods are summarized in the residual category "Others".

We provide a set of stylized facts regarding the relationship between income, consumption and emissions in the EU. In particular, our data suggests the following:

1. There is a non-proportional consumption-income relationship.
2. The composition of the consumption basket varies substantially across consumption deciles.
3. Even within consumption deciles, there is substantial heterogeneity in consumption basket composition.
4. For certain consumption categories there is additional variation in emission intensities within consumption deciles.

We now discuss these stylized facts in detail.

3.1 The income, consumption and emissions relationship

As a first step, Table 2 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 2 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".[12] 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 2: The cross-sectional relation between income and GHG emissions

	(1)	(2)	(3)
Income in €	0.324***	0.438***	0.555***
	(0.00628)	(0.0115)	(0.0169)
(Income in 1000€)^2		−0.792***	−2.088***
		(0.101)	(0.205)
(Income in 1000€)^3			1.809***
			(0.346)
Country FE	yes	yes	yes
N	256,299	256,299	256,299
R^2	0.415	0.449	0.464
R^2 expl. by income	0.283	0.310	0.320

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

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 3. 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.

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

Table 3: The cross-sectional relation between consumption and GHG emissions

	(1)	(2)	(3)
Consumption in €	0.669***	0.765***	0.841***
	(0.00284)	(0.00600)	(0.0167)
(Consumption in 1000€)^2		−1.219***	−2.997***
		(0.0923)	(0.443)
(Consumption in 1000€)^3			10.530**
			(2.941)
Country FE	yes	yes	yes
N	256,299	256,299	256,299
R^2	0.774	0.777	0.777
R^2 expl. by consumption	0.643	0.644	0.644

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

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 2. 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 2 and 3 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.

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 3 with additional control variables. Specifically, we control for 5-year household age bins, household size, education levels, labor market activity status, home-ownership, and regional population density. The results are shown in Table 4. 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).[13] In regression (2), we include additional controls. Accounting for these controls does not change the regression coefficient

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

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.

Table 4: Controlling for background characteristics

	(1)	(2)
Consumption in €	0.671***	0.648***
	(0.000816)	(0.00105)
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	243,222	243,222
R^2	0.773	0.776

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

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.

To better understand the mechanisms underlying the relationship between income, consumption, and emissions, we now examine the individual components of equation 1 in more detail. Specifically, we analyze how each component varies with income and consumption and how it contributes to the overall income, consumption and emissions relationship.

Table 5 reports the coefficients of variation (CV) for income, consumption, and emissions after controlling for country-fixed effects. The cross-sectional dispersion in income thus exceeds that of consumption, while the dispersion in emissions lies between the two, with an estimated CV of 0.56.

Table 5: Coefficients of variation

CV	Income	Consumption	Emissions
	0.635	0.521	0.562

Table 6 reports the pairwise correlation coefficients among consumption, income, and emissions. The correlation between income and consumption is relatively

modest, indicating that variation in income explains only a limited share of the variation in consumption. The correlation between consumption and emissions is higher, yet clearly below unity, implying that factors other than consumption also contribute to emissions. Consequently, the correlation between income and emissions is even weaker, suggesting that the income–emissions relationship is only indirectly mediated through consumption and additional unobserved determinants.

Table 6: Correlation Coefficients

Corr	Con_Inc	Con_Em	Inc_Em
	0.638	0.846	0.551

Figure 8 further illustrates the results for the relationship between consumption, income, and emissions. 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:

$$y_{i,p,c} = \gamma + \alpha_p + \kappa_c + \varepsilon_{i,p,c}, \tag{2}$$

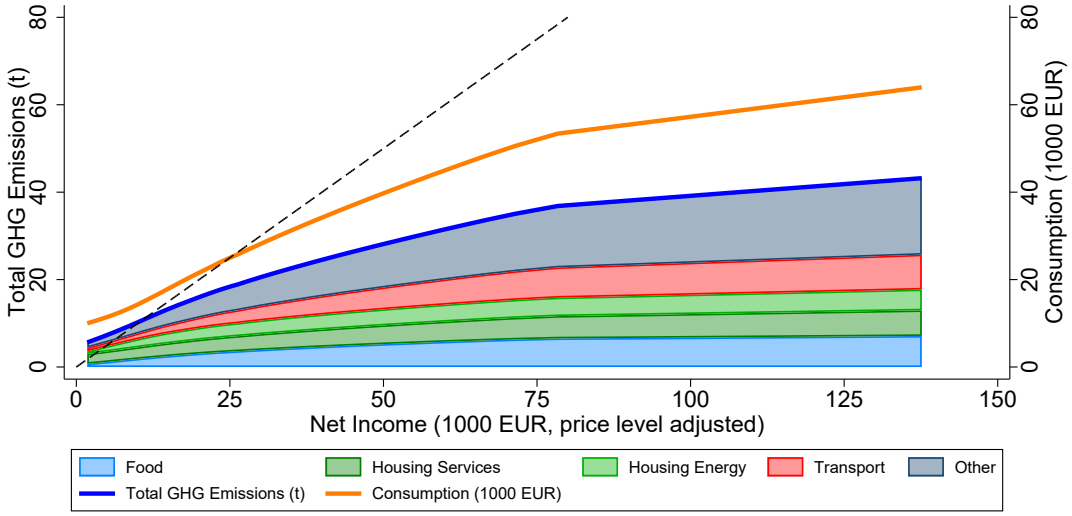
where y is a variable of interest for household i in income percentile p and country c. α_p denotes percentile fixed effects, κ_c denotes country fixed effects, γ is the intercept and $\varepsilon_{i,p,c}$ is the regression residual. As explanatory variables, we use either total household consumption, 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.5 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 3.

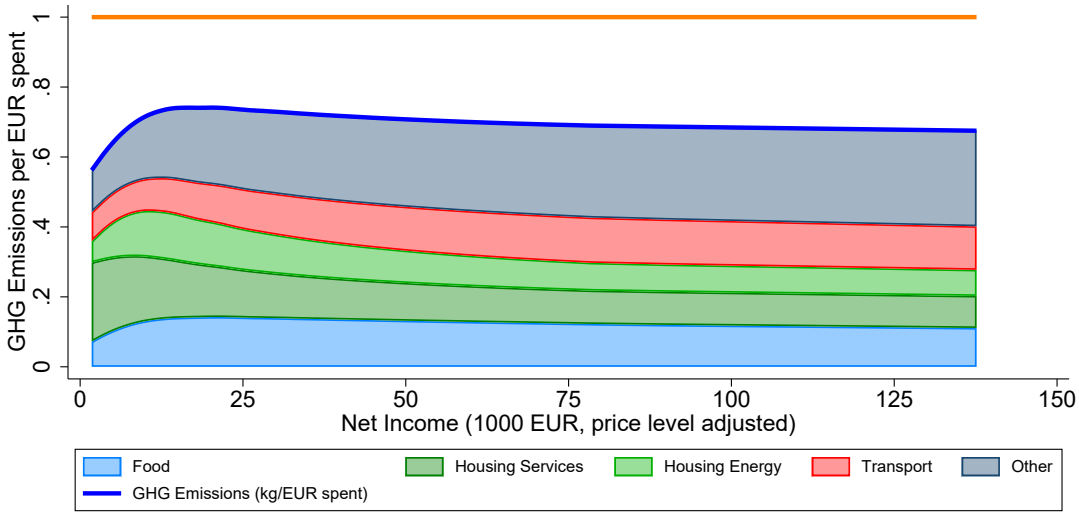
Panel (b) of Figure 8 sheds light on the relationship between consumption levels, consumption baskets, and emissions. To achieve this, we normalized all lines in Panel (a) by the level of household expenditure. The resulting lines in Panel (b) show household GHG emissions (in kg) per Euro of household spending. There are two key points to note. First, households at the lower end of the income

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 (2) 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.5 in Appendix D.

distribution generate slightly higher emissions per Euro spent compared to households at the upper end. The emissions intensity of consumption first rises along the income distribution from around 0.6 kg per Euro spent to 0.75 for an average net income of 10.000 euro and then declines back to 0.7 kg. This is a relatively small difference, consistent with the idea that consumption baskets play a higher

of a role in explaining within-country variation in carbon footprints. 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 0.4 out of the 0.7 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 rises from around 0.6 to 0.7 kg per Euro spent.

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 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 insights from this part of the analysis are formalized as stylized fact 1. 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.

3.2 The consumption basket across and within consumption deciles

The results in Figure 8 and Table 3 indicate that household consumption plays a substantially larger role than income in explaining variation in household carbon footprints.

We next examine the composition of the consumption basket along the consumption distribution, corresponding to the second component of equation (1). Figure 9 displays expenditure shares and corresponding emission shares across consumption deciles. Figure 9 shows the expenditure shares and corresponding emission shares over the consumption deciles. The figure illustrates substantial changes in the composition of the consumption basket across consumption deciles. In particular, the expenditure shares devoted to housing services and housing energy decline with consumption, whereas the share allocated to transportation increases. The expenditure share for food exhibits a hump-shaped pattern across deciles but remains relatively stable overall. The pattern of emission composition is again

similar to the one of consumption shares but there are also some noticeable differences in the emission shares across consumption deciles. These differences are likely driven by heterogeneity in emission intensities across product categories, particularly for housing energy and other goods and services.

Figure 9: Consumption basket and emission composition over consumption

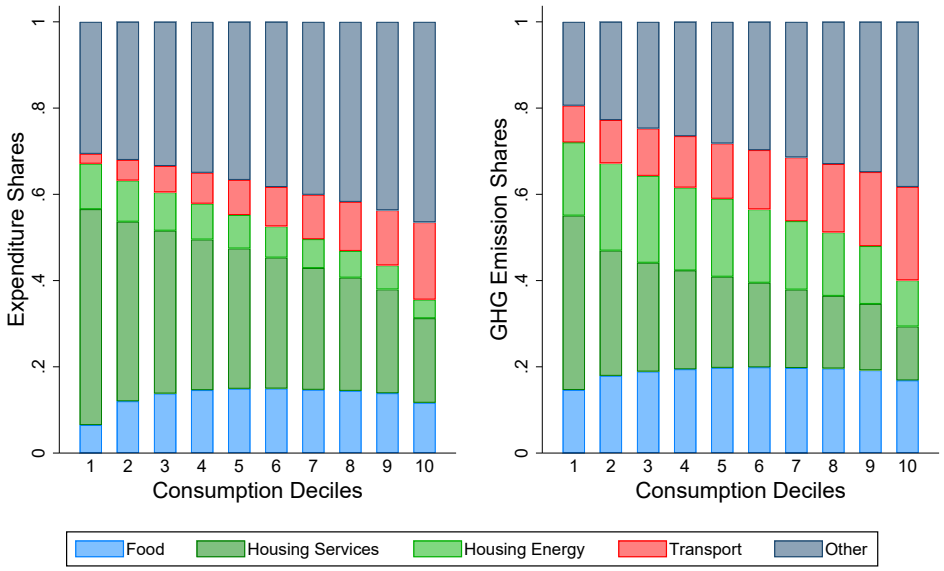


Table 7 shows the coefficients of variation in the single consumption components and corresponding footprints after controlling for country-fixed effects and consumption deciles. The table therefore captures residual variation within consumption deciles, after accounting for cross-country differences and average consumption levels, which we will refer to as "within decile CV" in the following. We find the lowest residual variation within deciles for the consumption of housing services, with a within decile CV of 0.34. It is especially high for the transportation sector with a within decile CV of 1.218. Overall, residual variation within consumption deciles differs considerably across consumption categories.

Table 7: Coefficients of Variation within consumption deciles

	Within decile CV				
	Food	Housing Services	Housing Energy	Transport	Other
Consumption	0.784	0.340	0.665	1.218	0.348

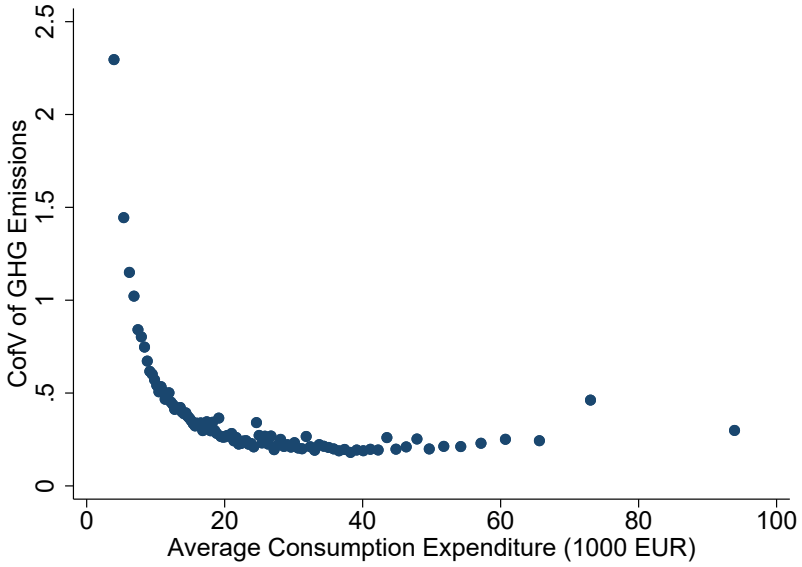
The insights from this analysis lead us to formulate stylized facts 2 and 3. Taken together, these results highlight both systematic differences across the consumption distribution and considerable heterogeneity among households with similar

consumption levels. We now turn to heterogeneity in emissions conditional on total consumption, corresponding to variation in emission intensities and residual basket heterogeneity in equation (1).

3.3 Heterogeneity in carbon footprints conditional on consumption

Even after controlling for the household's consumption level, substantial heterogeneity in carbon footprints across households remains. Figure 10 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 equation (2), 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.

Figure 10: 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.

For all consumption percentiles above the 20th percentile, the coefficient of variation remains relatively stable, ranging between 0.25 and 0.30. 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 suggests that heterogeneity in consumption baskets plays a much larger role for this segment of the population compared to the upper four quintiles of the consumption distribution.

Table 8 reports the coefficients of variation for individual consumption categories from Table 7 and their associated carbon footprints, conditional on country fixed effects and consumption deciles. For most consumption categories, emissions exhibit greater within-decile heterogeneity than expenditures. This difference is particularly pronounced for housing energy and the category of other goods and services. We can also note that there is quite some variation across the consumption goods: the coefficients of variation for consumption and emissions are relatively similar for the food and housing services categories. Transportation shows high variation within deciles both in terms of emissions and consumption. Taken together, these results indicate that variation in consumption patterns alone is insufficient to account for the observed heterogeneity in household carbon footprints, as formalized in stylized fact 4.

Table 8: Coefficients of Variation within consumption deciles

	Within decile CV				
	Food	Housing Services	Housing Energy	Transport	Other
Consumption	0.784	0.340	0.665	1.218	0.348
Emissions	0.712	0.353	1.629	1.234	0.585

In summary, even 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 and consumption distributions and unsystematic variation of consumption behavior within consumption deciles. Systematic variation comes from the fact that lower-income households devote relatively larger expenditure shares to food, housing services, 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.

3.4 Summary of empirical analysis

In Section 2.5 and in this section we saw that in our data income and carbon inequality are only weakly correlated across EU countries and that consumption and income are not the same. Figure 8 clearly illustrated that income poor households typically consume more than their instantaneous income whereas people at the top save. The consumption basket changes along the consumption distribution and even after accounting for income, consumption and the consumption basket, there is still considerable residual heterogeneity in carbon emissions across

households. Our stylized facts indicate that household-level carbon emissions are driven by several distinct mechanisms: a non-linear relationship between income and consumption; systematic variation in consumption baskets across consumption deciles; substantial heterogeneity in consumption patterns within consumption deciles; and additional variation in emission intensities for specific goods, both across and within consumption deciles.

A model that aims to replicate the observed patterns in the data must account for all of these dimensions of heterogeneity. We can motivate this using our data by implementing a simple decomposition exercise.

We find that these three elements can vary considerably along the income distribution, but also across countries. Figure D.6 shows scatterplots that illustrate the relationship between income inequality and emission inequality, where we calculate the Gini of both income and GHG emissions across countries. The blue dots show the relationship between income inequality and emission inequality that we can see from the data, where we have variation in all components described in equation (1). Suppose instead that all households share the average income–consumption relationship, the average consumption basket, and average emission intensities. We therefore take out the variation in all of the three components described in equation (1). In this case, inequality in GHG emissions mechanically coincides with income inequality. This can be seen in Panel a) of Figure D.6, where the data points are directly on top of the 45°-line if we take out the variation in all three components. In a next step we only take out the variation in emission intensities across households, so allow for the variation in the consumption-income relationship and in their consumption basket that we see in the data, but we assume that households have average emission intensities. The effect of this is displayed in Panel b) of Figure D.6. We can see that only allowing for different consumption patterns and consumption baskets (so without accounting for variation in emission intensities) leads to the break between income and GHG emissions that we described in the previous sections. However, in almost all countries this specification substantially understates observed inequality in GHG emissions.[14] This is because on top of the consumption basket and the consumption-income relationship there is a serious heterogeneity in the emission intensity of households that consume different goods. We can do the same exercise w.r.t the other two components and look at the effects of taking out the variation in the consumption-income relationship and in the consumption basket of households. Those results are displayed in Panel c) and d) of Figure D.6, respectively.

This exercise demonstrates that accurately replicating carbon inequality across countries requires accounting for heterogeneity in all three components of the decomposition. Importantly, the empirical analysis above is purely descriptive and does not identify causal mechanisms. Rather, it documents a set of robust patterns in the data that any quantitative framework aiming to study carbon inequality

[14]The exception from this is Cyprus, where the inequality in emissions is now overestimated.

should be able to replicate. In Section 4, we therefore introduce a structural model that is designed to provide a coherent economic framework for these patterns. The purpose of the model is not to establish causal identification, but to map the observed heterogeneity in income dynamics, consumption behavior, and emission intensities into a unified setting that can be used for quantitative analysis.

4 A quantitative model

In the following we develop a general equilibrium life-cycle model that reflects the empirical insights from our data and enables a more detailed examination of the link between income and carbon inequality. The model is designed as a quantitative framework that organizes and replicates the empirical patterns documented in the previous section, rather than as a tool for causal identification. In particular, each model component directly corresponds to one of the stylized facts established in Section 3. We explicitly incorporate the substantial heterogeneity across EU member states documented in Section 2.4. Section 2.5 showed that 86% of the variation in total emissions occurs within countries, which could, in principle, be captured by an EU-wide model with a single representative country. Yet, when considering individual emission components, there is also pronounced cross-country inequality in emissions. This is particularly true for housing energy, where 36.5% of inequality arises between EU countries. To capture these patterns, we design our model to include 26 countries.[15] The model structure and the corresponding households optimization problem are constructed in line with the stylized facts presented in Section 3. Wealth accumulation plays a central role in the model, as it permits households to shift consumption—and hence carbon emissions—across time. We then use the model to characterize the present value distribution of carbon emissions along the income and wealth distribution. This, in turn, provides a tractable framework for analyzing the distributional and welfare implications of carbon pricing in subsequent applications.

4.1 Household optimization problem

According to stylized fact 1 a model that is able to accurately display the carbon footprint of households needs to account for a non-proportional link between income and consumption. Figure 8 in Section 3.1 shows that households with low income tend to consume more than their income and higher income households tend to consume less than they earn. This pattern is consistent with households that use their savings and accumulated wealth to smooth consumption over time. A purely static framework will not be able to achieve the empirically ob-

[15] We base our analysis on 26 rather than 27 EU countries because, to the best of our knowledge, income data for Italy are only available in decile form. This level of aggregation is too coarse for the degree of precision required in our analysis, and Italy is therefore excluded from the model.

served discrepancy between household income and consumption. Since the carbon emissions of households are mainly determined by their consumption patterns rather than their income levels, a static model would mechanically misrepresent the relationship between income, consumption, and emissions. Capturing such behavior requires a dynamic framework in which households make intertemporal consumption-savings decisions. Moreover, in the presence of income risk, forward-looking households engage in precautionary savings, further weakening the link between current income and consumption. In what follows, we describe how our framework incorporates this mechanism. As a first step, we set up the household optimization problem for agents residing in a single representative country. Country-specific parameters will be introduced at a later stage.

4.1.1 Preferences and the Budget Constraint

Preferences The model features an overlapping-generations structure with heterogeneous agents, following Auerbach and Kotlikoff (1987). In each period, a new cohort enters the economy. A household lives for J years and we denote the age of an household by $j = 1, \ldots, J$. Households start their working life at age $j = 20$ and we allow for a maximum life span of $J = 80$ years.[16] Retirement occurs at age J_r. Each cohort consists of a continuum of households with measure 1.

Households have identical preferences over stochastic streams of consumption bundles $c_j \geq 0$. For the sake of simplicity, it is assumed that households labor decisions are inelastic so that they provide exactly one unit of labor of $l = 1$ in each period. They maximize the discounted expected utility

$$U_0 = E\left[\sum_{j=1}^{J} \beta^{j-1} u(c_j)\right],$$

where households discount the future with the constant time discount factor β. In the following we will define the aggregate consumption bundle c_j in more detail. Let us first note that this dynamic setting with income risk will achieve the intended non-linear consumption-income relationship where households undertake precautionary savings to smooth their consumption over time. This will lead to some households consuming less than they earn and some households consuming more than they earn, accounting for stylized fact 1.

Households consume different goods c_{jg} at prices q_g, where $g = 1, \ldots, G$ is the respective good in the consumption bundle. The model also needs to account for variation in the composition of the consumption baskets across consumption deciles, as established by stylized fact 2. To model these differences, there are two main approaches in the literature. The first approach is to use Stone-Geary

[16] This corresponds to the average remaining life expectancy at age 20 across EU countries being 60.1 years, based on data from the Human Mortality Database (2024). This implies a maximum lifespan of approximately age 80.

preferences, going back to Geary (1950) and Stone (1954) and formalized by Gorman (1961). Their idea was to introduce subsistence levels of consumption for the different goods. However, using Stone-Geary preferences did not generate the necessary variation across the consumption distribution that correspond to the data. This lead us to adopt the second approach, which is the more recent class of non-homothetic CES aggregators, as in Comin et al. (2021). Following this approach, the utility function is given by

$$u(c_j) = \frac{c_j^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}}$$

where the aggregate consumption bundle/ non-homothetic CES aggregator c_j is defined by the following equation:

$$\sum_{g=1}^{G} \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} = 1. \tag{3}$$

The parameters Ω_g in equation (3) are the weights of the g different goods in the consumption basket and ϵ_g is the non-homotheticity parameter of the respective good. If $\epsilon_g = 1 \quad \forall g$, then this aggregator is a standard CES aggregator across the different goods where each good has a weight (the Ω_g's) and can only be substituted to a limited extent, determined by the CES elasticity of substitution σ. In this case, the households preferences are homothetic. This means that if income doubles and prices remain constant, the consumption of each good doubles proportionally and expenditure shares on each good stay constant as income rises. Into the setting of the standard CES aggregator, we now introduce the additional parameter epsilon. When $\epsilon_g \neq 1$, preferences for this good are non-homothetic. This means that the importance of the good changes with income. Goods with $\epsilon_g < 1$ behave like necessities, so they are consumed relatively more at low income levels and their expenditure share declines as income rises. Goods with $\epsilon_g > 1$ behave like luxuries, so their expenditure share rises with income. Thus, this non-homotheticity parameter can be interpreted as governing the income elasticity of demand for each good: the lower ϵ_g is, the less responsive consumption of good g is to income growth, and the more concentrated consumption of that good is at low income levels. This captures the classic distinction between necessity and luxury goods and allows us to replicate the heterogeneity in the households consumption baskets that we saw in the data. We treat $g = 5$, the Other goods and services category, as the base good, i.e. $\Omega_5 = 1$ and $\epsilon_5 = 1$. This formulation allows expenditure shares to vary with the level of consumption while still keeping the flexibility of the constant elasticity of substitution assumption. This setting therefore allows for changes in the consumption basket according to stylized fact 2.

Budget constraint Households are ex ante homogeneous, but differ ex post in their labor productivity. All individuals share a common deterministic, age-

specific labor earnings profile κ_j. Throughout working life ($j < J_r$), they are exposed to shocks on their labor productivity $\exp(\eta_t + \nu_t)$ and thus on their labor income, which depends on both a persistent and a transitory component. The idiosyncratic shock to labor productivity η follows an AR(1) process,

$$\eta^+ = \rho\eta + \varepsilon^+, \qquad \varepsilon^+ \sim N(0, \sigma_\varepsilon^2), \tag{4}$$

where ρ governs the persistence of labor earnings shocks. In addition to this persistent shock, households face a transitory shock on labor productivity $\nu \sim N(0,\ \sigma_\nu^2)$ that is iid across households and over time. Gross labor earnings of a household consequently read

$$y = w\kappa_j \exp(\eta + \nu),$$

where w is the wage rate per labor efficiency unit. After retirement ($j \geq J_r$) households no longer supply labor and instead receive retirement income. In the model this retirement income is represented as a government transfer that depends on the persistent productivity component at the time of retirement. In particular, the transitory shock no longer affects income after retirement. This reduced-form specification captures the empirical link between lifetime earnings and pension benefits without explicitly modeling the pension system. Households can save their capital a in a risk-free asset that pays a return r in order to smooth their consumption over time. The budget constraint of a household reads

$$a^+ + \sum_{g=1}^{G} q_g c_{jg} = (1 + r)a + w\kappa_j \exp(\eta + \nu). \tag{5}$$

4.1.2 Taste Shifters

We established that even within a given consumption decile, households differ substantially in how they allocate their budgets across the different goods, as formalized in stylized fact 3. To capture this, we introduce heterogeneity in preferences across the households, in the sense that some households just naturally prefer the consumption of one good over the other. The weight of each good g in the CES aggregator is given by

$$\Omega_g = \bar{\Omega}_g + \omega_g. \tag{6}$$

has a baseline taste weight $\bar{\Omega}_g$ in the CES aggregator and an idiosyncratic deviation ω_g with $E[\omega_g] = 0$ and $\text{Var}[\omega_g] = \sigma^2_{\omega,g}$ that is iid across the products g. Economically, these taste shifters capture persistent differences in lifestyles, habits and local environments. This structure allows the model to reproduce the observed variation in consumption shares within deciles, not just across them.

4.1.3 Emissions and Footprint Shifters

Emissions We have not yet established how emissions arise in this model. For now, emissions arise simply due to consumption of goods. Each of the g goods has a specific emission factor $\Phi_g > 0$. Emissions of a household are therefore given by the following emission function:

$$em_j = \sum_{g=1}^{G} \Phi_g \cdot c_{jg}. \tag{7}$$

Footprint Shifters In Section 3 we saw that there is also heterogeneity in those good-specific emission intensities that could, for example, be due to differences in the product quality, production technology or energy sources of the good. We saw that this variation in emission intensities is important and necessary to correctly model the inequality in GHG emissions and formalized this as stylized fact 4. To capture this we introduce heterogeneity in the emission intensities Φ_g, which are defined by

$$\Phi_g = \bar{\Phi}_g + \phi_g. \tag{8}$$

We therefore assume that each good has a baseline emission factor $\bar{\Phi}_g$ and an idiosyncratic deviation ϕ_g with $E[\phi_g] = 0$ and $\text{Var}[\phi_g] = \sigma^2_{\phi,g}$ that are iid across the products g.This will account for the additional variation in emissions of some goods that cannot be explained by consumption patterns, as formulated in stylized fact 4.

4.1.4 Country-specific parameters

Finally, let us introduce the parameters that are country specific and to which we add the index $c = 1, \ldots, 26$ for the respective country. From the data we know that the consumption-income relationship is different for each country. We account for that by allowing for differences in the parameters of the income process $(Var(\log y)^c, \sigma^2_\epsilon, \sigma^2_\nu)$, pension age (J^c_r) and the earnings process (κ^c_j). To model the respective changes in the consumption basket, we calibrate the parameters of the non-homothetic preferences $(\bar{\Omega}^c_g, \epsilon^c_g)$ for each country. Finally, the taste-shifters (ω^c_g) in equation (6) as well as average emission intensities $(\bar{\Phi}^c_g)$ and footprint shifters (ϕ^c_g) in (8) vary by country. After setting up the dynamic optimization problem in the next section, the following section presents the market structure. This structure is kept as simple as possible while simultaneously allowing for differences in prices of the G goods. As a result, households in each country face different consumer prices q^c_g.

4.1.5 The dynamic optimization problem

The current state of a household is described by a vector $\chi = (j, a, \eta, \nu, \mathbf{\Omega}, \mathbf{\Phi}, c)$. This vector summarizes the household's asset state a, the states of the two shocks

on labor productivity η and ν, the age of the household j and the states of the good specific taste deviations $\mathbf{\Omega} = \{\omega_g\}_{g=1}^G$ and footprint deviations $\mathbf{\Phi} = \{\phi\}_{g=1}^G$ as well as the country c. The households final optimization problem thus reads

$$V(\chi) = \max_{c_j, \{c_{jg}\}_{g=1}^G, a^+} \frac{c_j^{1-\frac{1}{\gamma}}}{1-\frac{1}{\gamma}} + \beta E\left[V(\chi^+)|\chi\right] \tag{9}$$

$$\text{s.t.} \quad \sum_{g=1}^G \left[\Omega_g^c c_j^{(1-\sigma)\epsilon_g^c}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} = 1 \tag{10}$$

$$\text{and} \quad a^+ + \sum_{g=1}^G q_g^c c_{jg} = (1+r)a + w\kappa_j^c \exp(\eta+\nu), \tag{11}$$

$$\eta^+ = \rho\,\eta + \varepsilon^+, \quad \varepsilon^+ \sim N\Big(0,\ \sigma_\eta^2\Big), \tag{12}$$

$$\nu \sim N\Big(0,\ \sigma_\nu^2\Big), \quad \text{iid across households and over time.} \tag{13}$$

with $\chi^+ = (j+1, a^+, \eta^+, \nu^+, \mathbf{\Omega}, \mathbf{\Phi}, c)$, where the shocks on household's tastes for the goods $\mathbf{\Omega}^c$ and the respective emission intensities $\mathbf{\Phi}^c$ are given by equations (6) and (8).

The solution to the non-homothetic CES life-cycle model is derived in Section E.1 in the appendix. The optimal intratemporal allocations for the consumption of goods and total expenditure can be solved as depending on c_j and are given by

$$c_{jg} = \Omega_g^c \cdot \left[\frac{q_g^c}{e_j}\right]^{-\sigma} c_j^{(1-\sigma)\epsilon_g^c} \quad \text{and} \quad e_j = \left[\sum_{g=1}^G \Omega_g^c \left[q_g^c c_j^{\epsilon_g^c}\right]^{1-\sigma}\right]^{\frac{1}{1-\sigma}}.$$

The intertemporal Euler equation is given by

$$u'(c_j) \cdot \frac{c_j}{\bar{\epsilon} e_j} = \beta(1+r^+) E\left[u'(c_j^+) \cdot \frac{c_j^+}{\bar{\epsilon}^+ e_j^+}\middle|\chi\right]$$

with $u'(c_j) = c_j^{-\frac{1}{\gamma}}$ and where $\bar{\epsilon} = \sum_{g=1}^G \epsilon_g^c \cdot s_g$ is the average elasticity and $s_g = \frac{q_g^c c_{jg}}{e_j}$ is the expenditure share of good g.

4.2 Firm technology and Government sector

Since households interact with firms on the goods, capital and labor markets, the next step is to formulate the optimization problem on the firm side. The firms in each country c demand capital K^c and labor L^c to produce good Y^c according to the Cobb-Douglas production function

$$Y^c = \zeta K^{c\alpha} L^{c1-\alpha},$$

where α is the elasticity of production with respect to capital and where ζ denotes the aggregate level of productivity. Assuming perfect competition and a large number of identical firms producing in each economy, the maximization problem of a representative firm in country c can be considered below.

This representative firm chooses its optimal inputs of capital and labor to maximize its profit π^c. It sells its output Y^c on the goods market at the constant producer price $p^c = 1$ and must pay the prices r and w for capital and labor. In addition, capital is depreciated at a constant rate δ. The maximization problem of the representative firm in country c is therefore

$$\max_{K^c, L^c} \ \pi^c = \zeta K^{c\alpha} L^{c1-\alpha} - (r+\delta)K^c - w\, L^c.$$

This leads to the following first-order conditions:

$$r = \zeta\alpha \left(\frac{K^c}{L^c}\right)^{\alpha-1} - \delta, \tag{14}$$

$$w = \zeta(1-\alpha) \left(\frac{K^c}{L^c}\right)^{\alpha}. \tag{15}$$

Since companies can invest the amount I^c in one period in order to increase the capital stock in the following period, the law of capital movements is given by the equation

$$K^{c+} = (1-\delta)K^c + I^c \tag{16}$$

is given. The investments must be made by the companies on the goods market.

4.3 Capital markets, Trade and Equilibrium

We model only a single asset market for the EU such that capital and goods are perfectly mobile across the countries. The optimization problem yields one market clearing international interest rate $\bar{r}$. All private savings that are not absorbed by the domestic production sector or the government are invested abroad at the interest rate $\bar{r}$. The capital market equilibrium for country c reads

$$K^c + Q^c = A^c, \tag{17}$$

where A^c are the country's aggregate private savings and Q^c is the country's net foreign asset position. When $A^c < K^c$ such that $Q^c < 0$, foreign investors hold claims on a fraction of the domestic capital stock. In the steady state, the associated net factor payments to the foreign sector are then given by $\bar{r}Q^c$, implying a trade balance of

$$TB^c = -\bar{r}Q^c. \tag{18}$$

On the goods market, total output produced by domestic firms is allocated to private consumption, investment, public consumption, and net exports. Accordingly, the goods market clearing condition is given by

$$Y^c = C^c + I^c + G^c + TB^c, \tag{19}$$

where C^c denotes the country's private consumption, I^c its investment and TB^c the trade balance. We assume that government expenditure G^c captures the wedge between producer and consumer prices, reflecting taxes, subsidies, or other distortions. In particular, income received by households during retirement is treated as a government transfer and is implicitly captured within this reduced-form government sector, without explicitly modeling how these retirement transfers are financed.

The equilibrium of this competitive market is derived in Section E.2 in the appendix. Section E.3 defines the steady state of this model.

What still needs to be added:

- in a first instance, we assume no taxation on carbons: $\tau = 0$

5 Calibration

We simulate 26 economies, each representing one of the countries in our empirical sample (excl. Italy). For the parameterization of the model, we specify values for two distinct groups of parameters. First, we impose a set of parameters that are held constant across countries. These include selected preference parameters (such as the elasticities of substitution and the time discount factor), production technology parameters, and the exogenous world interest rate. Second, we assign country-specific parameters, encompassing the stochastic process for labor earnings, pension age, and additional country-level characteristics. These parameters are chosen to replicate salient features of our dataset. Parameters that cannot be directly identified from available data sources are determined via calibration.

In the following, we describe the calibration procedure in detail.

5.1 Country-invariant parameters

We calibrate the elasticity of intertemporal substitution γ to 0.5, which implies a coefficient of relative risk aversion equal to 2. The elasticity of substitution between goods σ is set to 0.3, following Comin et al. (2021). The subjective time discount factor β is fixed at 0.97.

We choose a depreciation rate of $\delta = 0.085$, which yields an investment-to-output ratio of approximately 21% that is consistent with empirical observations for EU countries. The exogenous international interest rate is set to $\bar{r} = 0.035$.

We normalize the technology parameter ζ such that the wage rate per efficiency unit of labor, w, equals 1. Under this normalization, the implied capital income share in production is $\alpha = 0.3$. Finally, we assume a country-invariant persistence parameter of $\rho = 0.95$ for the risk process η.

5.2 Country-specific parameters

Preferences We calibrate country-specific non-homothetic preference parameters $\left(\bar{\Omega}_g^c, \epsilon_g^c\right)$ for each consumption good g and country c so as to replicate the observed patterns of expenditure shares across the consumption distribution. The baseline taste weights $\bar{\Omega}_g^c$ primarily determine the average expenditure share of good g in country c. Let s_{gd}^c denote the expenditure share of good g in consumption decile d, and let D be the total number of deciles. We then target

$$\bar{s}_g^c = \frac{1}{D} \sum_{d=1}^{D} s_{gd}^c. \tag{20}$$

In the model, $\bar{\Omega}_g^c$ is set such that the model-generated average expenditure share matches this empirical counterpart while also accounting for its interaction with the other preference parameters.

The non-homotheticity parameters ϵ_g^c are calibrated to match how expenditure shares change across the consumption distribution. Specifically, we target the ratio of expenditure shares between the top two and bottom two income deciles:

$$\text{rel. } \mathrm{s}_g^c = \frac{\sum_{d=D-1}^{D} s_{gd}^c}{\sum_{d=1}^{2} s_{gd}^c}. \tag{21}$$

The parameter ϵ_g^c governs the sensitivity of expenditure shares to income and is chosen such that the model reproduces this relative expenditure share ratio.

Finally, the good-specific idiosyncratic taste shock ω_g^c are chosen to replicate the within decile coefficient of variation (Within decile CV) of consumption components. These within decile CVs for the EU as a whole were reported in table 7. We set ω_g^c such that the model-generated within-decile dispersion matches its empirical value for each country.

Labor earnings process In our model, gross labor earnings are specified (in logs) as

$$\log(y) = \log(w) + \log(\kappa_j^c) + \eta + \nu, \tag{22}$$

where $\eta^+ = \rho\,\eta + \varepsilon^+$ with $\varepsilon^+ \sim N\left(0,\ \sigma_\eta^2\right)$, and $\nu \sim N(0,\ \sigma_\nu^2)$ iid across households and over time. We normalized $w = 1$. We use information on labor earnings

in our dataset to estimate the life-cycle earnings profile κ_j^c separately for each country c. To do this, we proceed as follows: We use data on total household monetary net income from households with heads aged between 20 and 65. We first run a regression of log income on age fixed effects a_j^c to isolate the age-specific component of labor earnings. We then approximate these age effects using the flexible functional form

$$\log(\kappa_j) = \mu_0^c + \mu_1^c \times j + \mu_2^c \times \mathbb{1}_{j \leq J_l^c} \times \frac{(j - J_l^c)^3}{10000} + \mu_3^c \times \mathbb{1}_{j \geq J_u^c} \times \frac{(j - J_u^c)^3}{10000} \quad (23)$$

that adequately captures the properties of life-cycle earnings in all countries. We exogenously set the upper knot J_u^c, which may vary across countries. The remaining parameters are chosen to minimize a residual sum of squares between the age fixed effects a_j^c and the parameterized version of the age profile of labor earnings $\log(\kappa_j^c)$. Finally, we normalize the values of $\log(\kappa_j^c)$ such that each country's economy wide average earnings $\bar{y}^c$ is equal to 1. Retirement occurs at age J_r, which is country-specific. We calibrate J_r^c using data on the average age at first receipt of an old-age pension in 2012 from Eurostat (2019), thereby capturing cross-country institutional differences in effective retirement ages.

Income variance decomposition For each country c, we compute $\text{Var}(\log y)^c$ as the empirical weighted cross-sectional variance of log gross labor earnings using HBS data. We restrict the sample to households with heads aged between 20 and 60. Observations with non-positive earnings are excluded when computing log earnings. All moments are calculated using the provided survey weights. This empirical variance serves as the calibration target for the stochastic income process in the model.

Let $\text{Var}(\log y)^c$ denote the estimated variance from the data. We allocate this variance between the persistent and transitory components using a country-specific parameter $\theta^c \in [0, 1]$.

In the stationary distribution of the AR(1) process,

$$\text{Var}(\eta) = \frac{\sigma_\varepsilon^2}{1 - \rho^2}. \quad (24)$$

We choose σ_ε^2 and σ_ν^2 such that

$$\text{Var}(\eta) = \theta^c \, \text{Var}(\log y)^c \quad \text{and} \quad \sigma_\nu^2 = (1 - \theta^c) \, \text{Var}(\log y)^c. \quad (25)$$

This implies

$$\sigma_\varepsilon^2 = \theta^c \, \text{Var}(\log y)^c (1 - \rho^2). \quad (26)$$

Hence, θ^c governs the share of income inequality that is driven by persistent productivity differences, while $1 - \theta^c$ captures transitory earnings risk. We calibrate

θ^c so that the model reproduces the observed correlation between income and consumption, given the empirically estimated labor earnings profile and assuming a common persistence parameter of $\rho = 0.95$ across countries.

Consumer Prices To characterize cross-country differences in consumer prices, we draw on purchasing power parity (PPP) data from Eurostat (2024). The data report annual PPPs for detailed ESA 2010 consumption aggregates. From these data, we extract PPPs for five consumption categories that map directly into the goods in our model.[17]

The reported PPPs are expressed relative to the EU27 average. To obtain model-consistent relative prices within each country, we normalize the price vector such that the price of the "Other" category equals one in every country. All remaining good-specific prices are divided by the PPP of the "Other" category in the corresponding country. This preserves cross-country differences in relative price structures while ensuring a consistent within-country normalization.

While the model does not feature an explicit multi-sector production side, observed consumer prices reflect cross-country differences in production technologies, input costs, taxation, and market structure. By disciplining relative prices using PPP data, we incorporate supply-side heterogeneity in reduced form. Cross-country differences in consumption patterns therefore reflect not only preference heterogeneity, but also equilibrium price differences that embody underlying supply conditions. The resulting country- and good-specific price structure enters the household budget constraint and allows the model to account for observed variation in consumption price levels q_g^c.

Emissions Total household emissions in each country are determined by the emission function 7, where the emission intensities of goods Φ_g^c are specific to each country. To derive the country-specific baseline emission intensities $\bar{\Phi}_g^c$ used in equation 8, we estimate average emission intensities for the corresponding product categories from the data. The footprint shifters ϕ_g^c are subsequently calibrated so that countries match the within-decile coefficients of variation for each good. These within decile CVs for the EU as a whole were reported as part of table 8.

[17]The mapping to consumption aggregates is as follows: (i) food corresponds to "Food and non-alcoholic beverages"; (ii) housing services are proxied by the broader aggregate "Housing, water, electricity, gas and other fuels"; (iii) housing energy corresponds to the subcategory "Electricity, gas and other fuels," which is part of the broader housing aggregate; (iv) transport corresponds to "Transport"; (v) the residual category "Other" is approximated using actual individual consumption.

As no separate PPP series is available for housing services net of energy, we proxy housing services using the broader housing aggregate and separately include the energy subcomponent to isolate cross-country differences in energy prices. This allows the model to distinguish housing-related and energy-related price variation while remaining consistent with the available data classification.

6 Simulation Results

In this section, we present simulation results from our model. We start by comparing the stylized facts found in the data with the corresponding results from the model. Having established that our model provides an adequate fit to the data, we then turn to understanding how the model achieves this fit. To achieve this, we systematically decompose the contribution of each model component, quantifying its influence on the overall predictions and on key patterns in the data.

6.1 Cross-check of stylized facts

We assess the model's goodness of fit relative to the empirical data. The model-implied correlation between income and consumption at the country level is reported in Figure 11. The nonlinear relationship between income and consumption across countries is depicted in Figure 12. For this figure, we build on Figure 8 and normalize all variables by the average total household net income in the respective country. The displayed country-specific relationship between consumption and income was not imposed as a direct calibration target, but rather an outcome of the model. The model replicates the empirical relationship well for the majority of countries, with only a limited number of notable deviations. The cross-country composition of the consumption basket is shown in Figure 13, which reports expenditure shares by consumption decile. For each country, the left panel displays the observed data, while the right panel presents the corresponding model-generated outcomes. Table 9 summarizes the within-decile variation in consumption for the illustrative case of France. We obtain a similarly close fit to these calibration targets for all remaining countries. A comprehensive summary of the calibration targets for every country will be provided in the appendix.

Having shown that our model fits the data sufficiently well, we now focus on understanding how this fit is achieved. In the following section, we methodically break down the contribution of each model component, quantifying its impact on the overall predictions as well as on key patterns observed in the data.

We systematically decompose how each stylized fact and its associated model component affects the correlation structure implied by the model. Table 10 reports, for the illustrative case of France, the pairwise correlation coefficients between consumption, income, and emissions, as well as the R^2 statistics from simple linear regressions of emissions on income and on consumption. We begin with a baseline life-cycle model in which households draw a persistent income type ex ante that remains fixed over the life cycle. Formally, this corresponds to an identity transition matrix and the absence of transitory income shocks. In this setting, all income heterogeneity is deterministic and persistent. As a result, consumption closely tracks income, and emissions are perfectly tied to consumption, leading to correlations close to one. In the next step, we introduce persistent income risk by allowing households to transition between income states. While income remains

purely persistent, this additional uncertainty induces precautionary behavior and consumption smoothing, thereby reducing the correlation between income and consumption. However, consumption and emissions remain tightly linked. We then augment the model with transitory (iid) income shocks. Income risk now consists of both persistent and transitory components, governed by the relative variance of each. This further strengthens consumption smoothing and leads to a substantial decline in the correlation between income and consumption. Nevertheless, in the absence of non-homothetic preferences, emissions remain almost perfectly correlated with consumption. Introducing non-homothetic preferences constitutes the first mechanism that decouples consumption from emissions. By allowing expenditure shares to vary systematically with the level of consumption, households with different income levels allocate spending differently across goods with heterogeneous baseline emission intensities. This reduces the correlation between consumption and emissions and, in turn, between income and emissions. Next, we incorporate taste shifters, which generate heterogeneity in consumption baskets even within narrowly defined consumption groups. While their primary role is to match within-decile dispersion in expenditure patterns, they also contribute to further weakening the link between consumption and emissions. Finally, we introduce additional variation in emission intensities through footprint shifters. This captures heterogeneity in carbon intensity conditional on expenditure and is essential for matching the empirical correlation between income and emissions. Taken together, the full model — combining life-cycle dynamics with both persistent and transitory income risk, non-homothetic preferences, taste heterogeneity, and stochastic emission intensities—successfully reproduces the joint correlation structure observed in the data.

A detailed version of this decomposition for all countries is provided in Appendix F.

What still needs to be added:

- ...

Table 9: Coefficients of Variation within consumption deciles in France

DATA vs. MODEL:	Within decile CV				
	FO	HS	HE	TR	OT
Consumption	0.640	0.421	0.672	1.192	0.359
	0.641	0.422	0.674	1.181	0.370
Emissions	0.769	0.421	0.735	1.727	0.400
	0.769	0.422	0.740	1.726	0.396

Figure 11: The correlation between income and consumption across countries

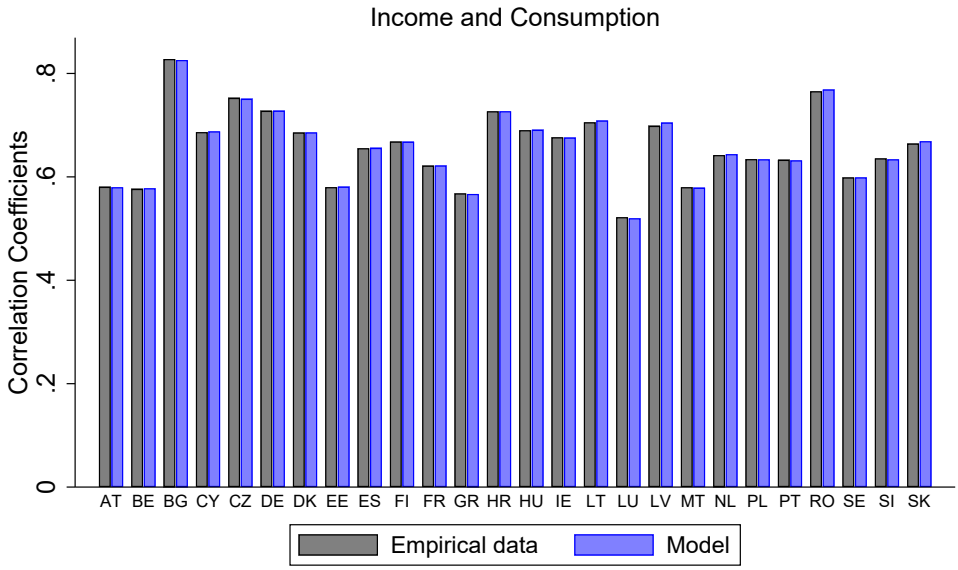
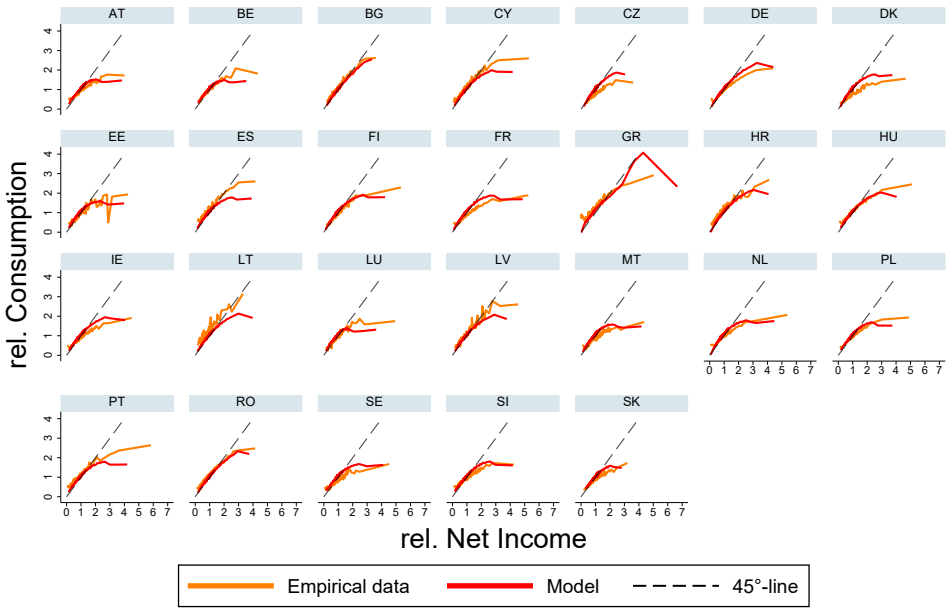
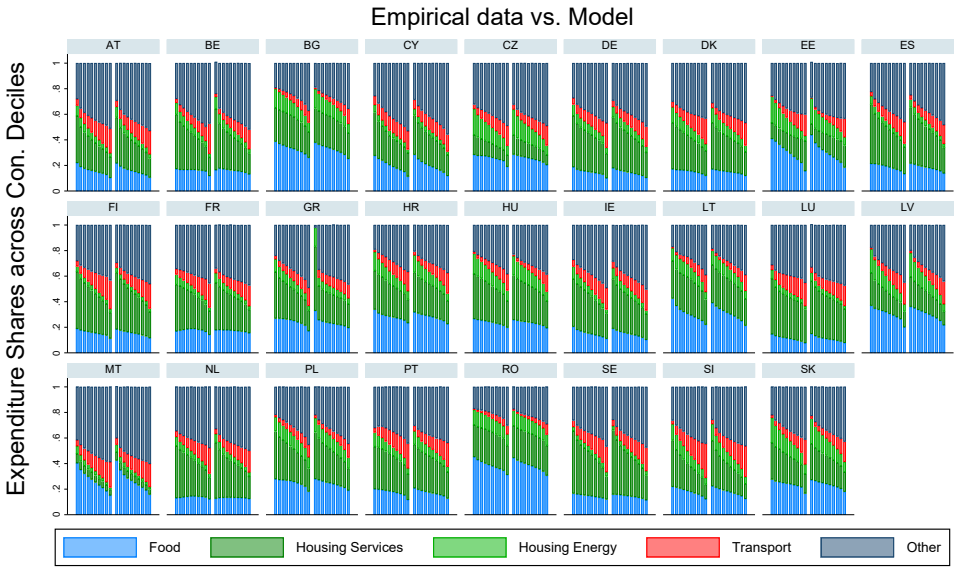


Figure 12: The relation between income and consumption across countries



Explanations: All variables were scaled by average total household monetary net income of the respective country.

Figure 13: Expenditure shares across consumption deciles across countries



Explanations: For each country, the graph on the left displays the observed data, while the graph on the right presents the corresponding model results.

Table 10: Decomposition of correlation patterns across model components in France

Country: France		**Correlation coefficient**			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.622	0.797	0.475	0.635	0.226
Model version:						
1	(Basic life-cycle model)	0.985	1.000	0.985	1.000	0.970
2	(+ persistent income risk)	0.864	1.000	0.864	1.000	0.747
3	(+ iid income shock)	0.624	1.000	0.624	1.000	0.389
4	(+ non-homotheticity)	0.622	0.998	0.619	0.996	0.383
5	(+ taste shifters)	0.622	0.960	0.597	0.922	0.356
Final	(+ footprint shifters)	0.622	0.807	0.501	0.651	0.251

6.2 Life-cycle behaviour

6.3 Carbon taxation

tba

7 Conclusion

Inequality in household carbon footprints across households in the EU is significant. In this paper, we explore the sources of this inequality and find that within-country inequality in GHG emissions is much larger than between-country inequality. Income, in general, is a poor predictor of household carbon emissions, both across and within countries. Our stylized facts indicate that household-level carbon emissions are driven by several distinct mechanisms: the non-linear relationship between income and consumption; systematic variation in consumption baskets across consumption deciles; substantial heterogeneity in consumption patterns within consumption deciles; and additional variation in emission intensities for specific goods, both across and within consumption deciles.

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 24, 2026

A Appendix: Details on data and matching procedures

A.1 The EXIOBASE environmentally extended supply-use tables

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,[18] 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

[18] 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)¨.

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.).[19] In total the EXIOBASE dataset 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:

$$CBA = S(I - A)^{-1}y \tag{27}$$

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[20]:

$$CBA^i = \sum_{s=1}^{m} CBA_s^i + \sum_{c=1}^{w} F_{Y_c}^i \tag{28}$$

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.

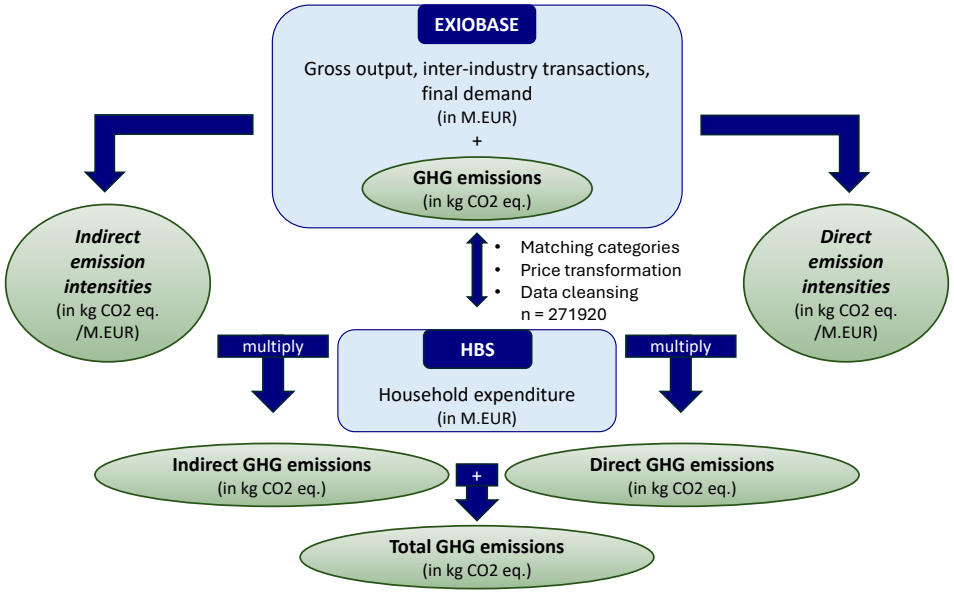
[19] One can think of the satellite account containing the raw data, for example on all the different greenhouse gases like carbon dioxide or methan. The impacts account then combines this data according to a certain metric, e.g. the GWP100, to indicate the greenhouse gas footprint of products in kg CO2-equivalents.

[20] 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.

A.2 Matching process of aggregate and individual level data

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 HBS. This includes the 27 EU member states for 2015, as well as the United Kingdom, Turkey and Norway. Table A.2 summarizes the countries covered in the two databases. We only included the EU27 in our final matching procedure and following analysis. A compact visualization of the whole matching procedure is displayed in Figure A.1.

Figure A.1: Matching procedure



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).[21] For example, one can assume that wood and wood products are predominantly used in the real estate construction sector. The alignment of the HBS

[21] 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

classification system and the EXIOBASE products to the chosen matching categories is summarized in Table G.15. 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 A.1.

A.2.1 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. [22]

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

$$y_{ic}^{pp} = y_{ic}^{bp} + t_{ic} + m_{ic} \quad \Rightarrow \quad y_{ic}^{bp} = \left(1 - \frac{t_{ic}}{y_{ic}^{pp}} - \frac{m_{ic}}{y_{ic}^{pp}}\right) y_{ic}^{pp}. \tag{29}$$

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".[23]

et al. (2023).

[22] 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.

[23] 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)".

Table A.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 Services**
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**

The corresponding expenditure share of net taxes minus subsidies, which can be

both positive and negative, was excluded from the further matching process.

A.2.2 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 case for 1149 out of the 279172 observations, as can be seen in Table A.3. 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.[24] 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 procedure 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.3 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 593 from other countries, see Table A.3. 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 A.3.2.

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[25]. 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

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

[25] 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).

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 intensities 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.

A.3 Special cases

A.3.1 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.[26] 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.

A.3.2 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

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

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 contained 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.

A.4 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 obser-

vations 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.[27] The observations that are dropped as part of the data cleansing process are summerized in Table A.3.

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

Table A.2: 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 A.3.2.
**: 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.3: 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	52412	50404*	71	—	1046	51295
DK	2186	—	103	—	40	2043
EE	3395	932	69	147	60	3119
ES	22130	1139	—	35	440	21655
FI	3673	—	1	—	72	3600
FR	16978	1183	59	338	330	16251
GR	6150	284	—	—	122	6028
HR	2029	—	—	—	40	1989
HU	7169	—	—	—	142	7027
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	279172	60119	1149	593	5510	271920

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 A.3.2.

B Appendix: Exploratory analysis of greenhouse gas emissions

B.1 Additional figures and tables

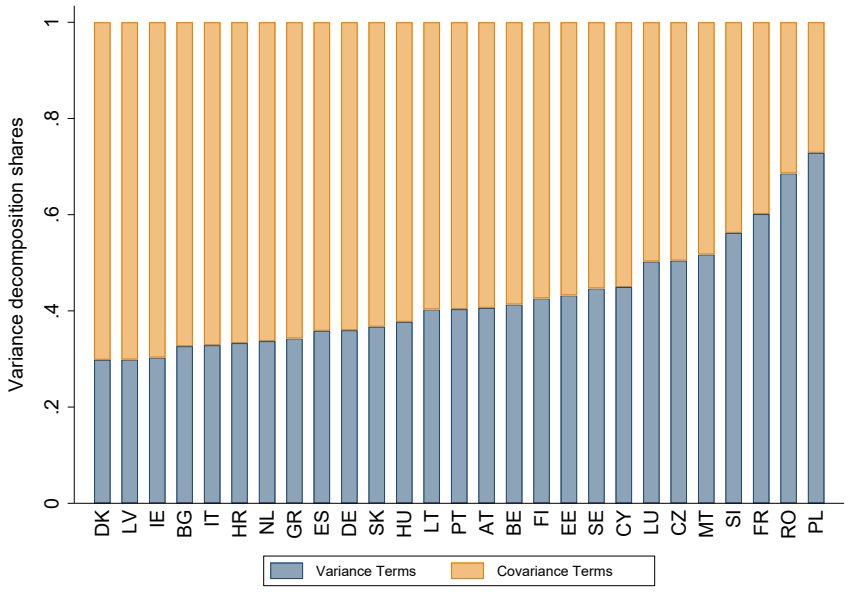
Table B.4: Average greenhouse gas emissions per consumption component

Component	**GHG emissions (kg)**	**Indirect (kg)**	**Direct (kg)**
Food	4,029	3,495	534
Housing Services	2,475	1,660	814
Housing Energy	2,938	2,769	169
Housing Cons.	1,048	863	185
Transp. Equim.	838	613	224
Fuels and Lubricants	1,269	1,166	103
Transp. Services	602	539	62
Restaurants/Hotels	953	624	329
Nondur. Cons.	2,120	1,711	409
Health	254	153	101
Education	94	43	51
Fin. Services	547	348	199
Other Goods and Services	504	325	179
Total	17,696	14,331	3,364

Table B.5: 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	11,618	5,840	46,635
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
DE	20,336	11,105	764,325
BE	21,133	10,459	100,004
DK	21,191	11,101	51,940
FI	21,636	11,591	56,563
PL	21,771	9,801	289,073
MT	22,148	9,081	3,572
EE	25,104	12,633	12,648
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	17,696	8,787	3,223,764

Figure B.2: 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

We conducted a principal components analysis of the within-country variation in household carbon footprints for the pooled sample of countries, see Table B.6.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 21% 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, 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 (C6) and education (C5) form a principal component that is orthogonal to any other consumption behavior.

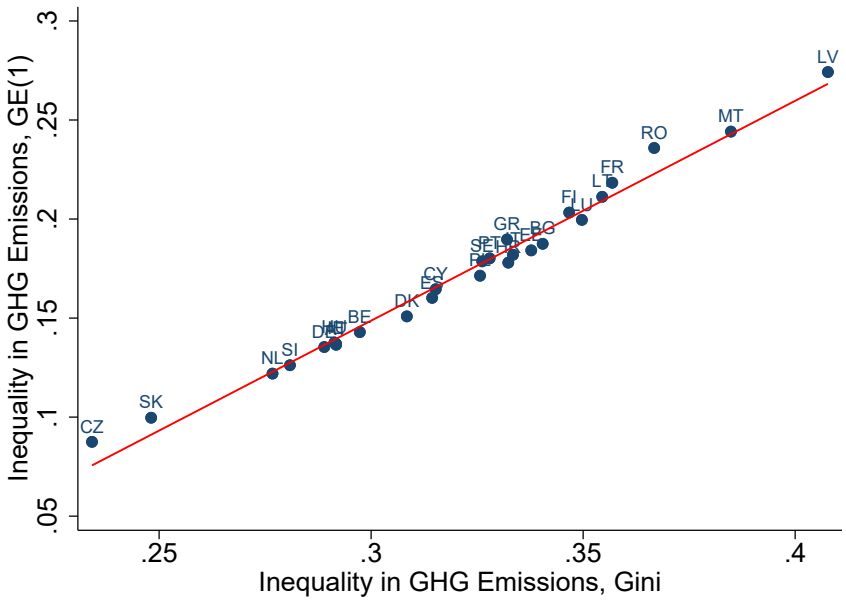
Table B.6: Principal components of within-country emissions inequality

	C1	C2	C3	C4	C5	C6
Proportion	0.21	0.08	0.08	0.08	0.07	0.07
Cumulative prop.:	0.21	0.29	0.37	0.44	0.52	0.59
Eigenvalue	2.71	1.04	1.03	0.98	0.96	0.92
Varimax rotated component loadings:						
Food	0.41	0.04	0.06	−0.12	0.05	0.12
Housing Services	0.21	−0.22	0.52	0.07	−0.02	−0.08
Housing Energy	−0.07	0.05	0.81	−0.02	0.00	0.03
Housing Cons.	0.50	−0.16	−0.11	−0.16	−0.11	0.06
Transp. Equim.	−0.05	0.68	−0.09	0.05	−0.05	0.03
Fuels and Lubricants	0.23	0.41	0.00	−0.12	−0.02	−0.11
Transp. Services	−0.02	0.00	0.00	0.91	−0.03	0.04
Restaurants/Hotels	0.35	0.05	−0.06	0.32	0.09	−0.17
Nondur. Cons.	0.47	0.07	−0.03	0.09	0.06	0.05
Health	0.01	0.01	0.01	0.03	0.01	0.96
Education	0.00	−0.01	0.00	−0.02	0.98	0.00
Fin. Services	−0.01	0.53	0.23	−0.03	0.03	0.03
Other Goods and Services	0.37	0.02	0.03	0.01	−0.05	−0.03

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.

C Appendix: Emissions inequality between and within countries

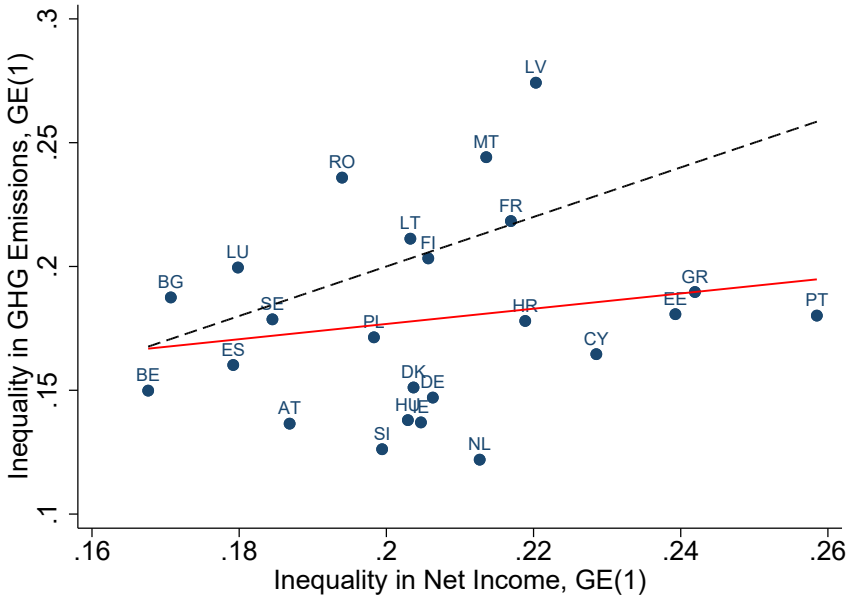
Figure C.3: Gini vs. $GE(1)$ index of the household carbon footprint



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.

Figure C.4: Correlation of emissions and household net income, excluding the Czech Republic and Slowakia



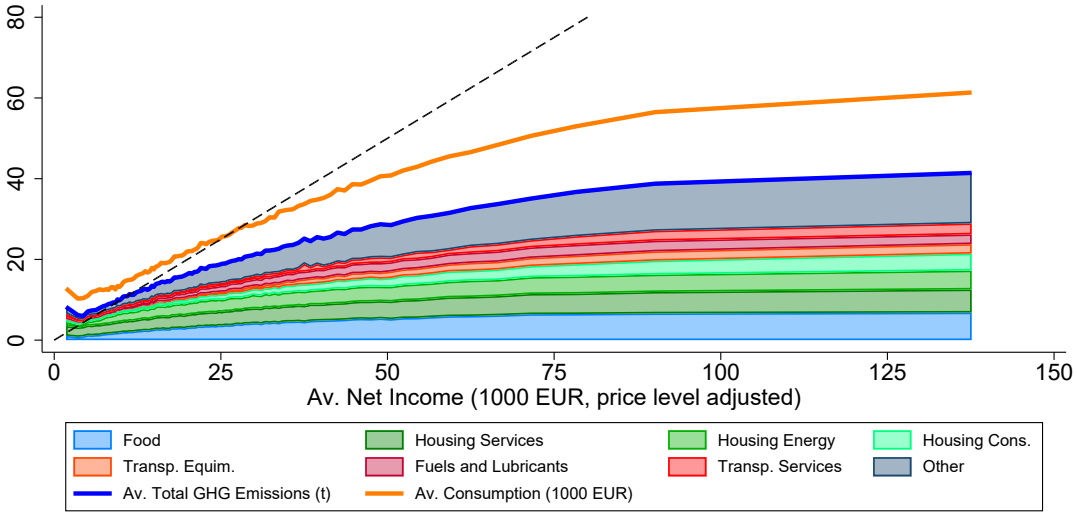
Estimated slope: 0.31, R^2: 0.03

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.

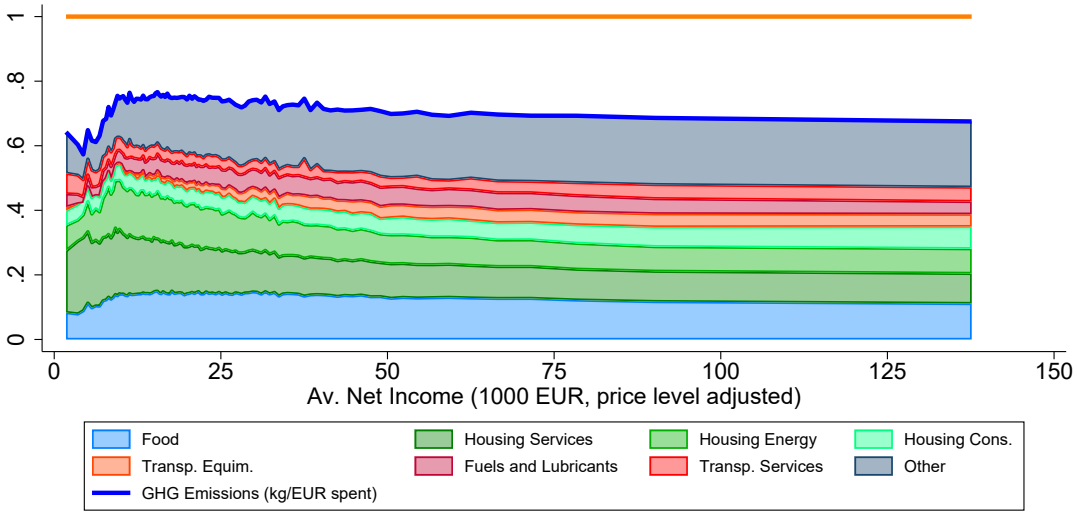
D Appendix: The income, consumption and emissions relationship

Figure D.5: 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.

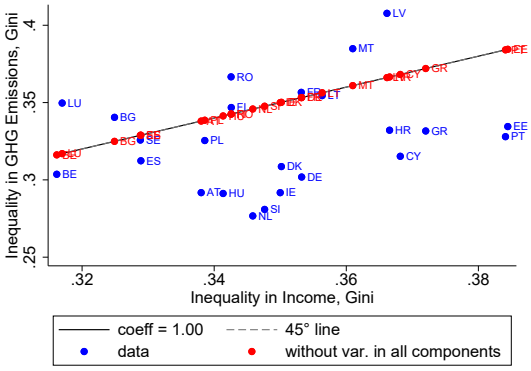
Table D.7: Regression outputs for expenditure

	(1) F_{total}	(2) F_{total}
Exp	0.671 (0.000816)	0.648 (0.00105)
$Country\ FE$		yes
Homeowner		2.614 (32.23)
$HHsize2$		678.855 (33.09)
$HHsize3$		1105.168 (45.24)
$HHsize4$		1233.160 (51.33)
$HHsize5$		1231.354 (71.60)
$HHsize6+$		1301.434 (98.43)
$Density\ interm.$		-209.849 (29.17)
$Density\ sparse$		-878.053 (31.61)
$Active1$		-170.597 (41.23)
$Active2$		-67.020 (49.33)
$Active3$		229.276 (76.51)
$Active4$		361.911 (127.71)
$Active5$		972.318 (285.69)
$Education1$		140.646 (104.92)
$Education2$		182.887 (104.76)
$Education3$		74.292 (103.86)
$Education4$		748.949 (108.6)
$Education5$		-176.220 (112.73)
$Education6$		651.917 (108.35)
$Education7$		626.991 (111.21)
$Education9$		422.631 (113.95)
$Age5_{27}$		169.985 (85.25)
$Age5_{32}$		504.067 (82.04)
$Age5_{37}$		355.431 (81.44)
$Age5_{42}$		329.291 (80.6)
$Age5_{47}$		382.466 (80.26)
$Age5_{52}$		305.880 (79.74)
$Age5_{57}$		343.822 (79.9)
$Age5_{62}$		275.455 (80.67)
$Age5_{67}$		152.246 (83.48)
$Age5_{72}$		-12.165 (85.27)
$Age5_{77}$		-145.257 (82.56)
_cons	-120.808 (72.11)	-264.331 (141.39)
N	243222	243222
R^2	0.773	0.776

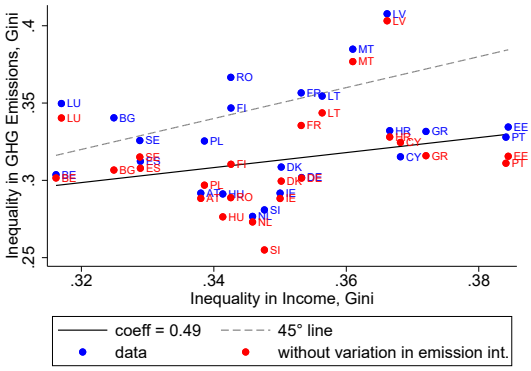
Explanations: Tba! Consumption expenditure has been price level adjusted using the price level conversion factors from Eurostat for ESA 2010 aggregates for 2015. Sample restricted to observations with non-missing observables. Robust standard errors are reported in parentheses.

Figure D.6: Decomposition of the inequality in GHG emissions

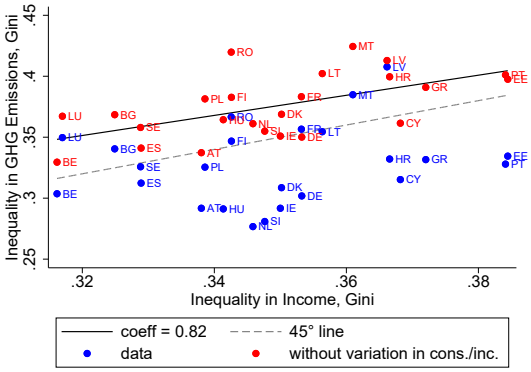
(a) Without variation in any of the components



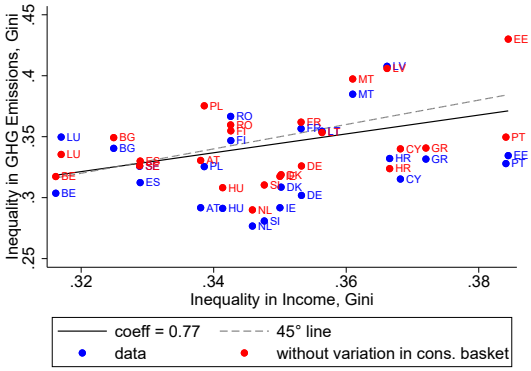
(b) Without variation in emission intensities



(c) Without variation consumption-income relationship



(d) Without variation in consumption basket



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

E Appendix: Model

E.1 Solution to the household optimization problem

- The household optimization problem reads

$$V(\chi) = \max_{c_j, \{c_{jg}\}_{g=1}^{G}, a^+} \; u(c_j) + \beta E\left[V(\chi^+)|\chi\right] \tag{30}$$

$$\text{s.t.} \quad \sum_{g=1}^{G} \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} = 1 \tag{31}$$

$$\text{and} \quad a^+ + \sum_{g=1}^{G} q_g c_{jg} = (1+r)a + w\kappa_j \exp(\eta+\nu) \tag{32}$$

$$\eta^+ = \rho\,\eta + \varepsilon^+, \quad \varepsilon^+ \sim N\left(0,\ \sigma_\eta^2\right), \tag{33}$$

$$\nu \sim N\left(0,\ \sigma_\nu^2\right), \quad \text{iid across households and over time.} \tag{34}$$

- The Lagrangean of the problem (for a working household) reads

$$\begin{aligned}\mathcal{L} = {} & u(c_j) + \beta E\left[V(\chi^+)|\chi\right] \\ & + \lambda_1 \left[\sum_{g=1}^{G} \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} - 1\right] \\ & + \lambda_2 \left[(1+r)a + w\kappa_j \exp(\eta+\nu) - a^+ - \sum_{g=1}^{G} q_g c_{jg}\right]\end{aligned}$$

- Let us define household consumption expenditure as $e_j = \sum_{g=1}^{G} q_g c_{jg}$

- First-order conditions read:

$$u'(c_j) = \lambda_1 \cdot \frac{\sigma-1}{\sigma} \cdot \sum_{g=1}^{G} \epsilon_g \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} \cdot \frac{1}{c_j} \tag{35}$$

$$\lambda_2 q_g = \lambda_1 \cdot \frac{\sigma-1}{\sigma} \cdot \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} \cdot \frac{1}{c_{jg}} \tag{36}$$

$$\lambda_2 = \beta E\left[V_a(\chi^+)|\chi\right] \tag{37}$$

- Summing up (36) over all goods g we get

$$\lambda_2 \underbrace{\sum_{g=1}^{G} q_g c_{jg}}_{=e_j} = \lambda_1 \frac{\sigma-1}{\sigma} \cdot \underbrace{\sum_{g=1}^{G} \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}}}_{=1} \quad \Rightarrow \quad \lambda_2 e_j = \lambda_1 \frac{\sigma-1}{\sigma}$$

- Using this again in equation (36), we obtain the expenditure share

$$s_g = \frac{q_g c_{jg}}{e_j} = \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}}$$

- Solving the expenditure share for c_{jg}, we get the consumption of good g as

$$c_{jg} = \Omega_g \cdot \left[\frac{q_g}{e_j}\right]^{-\sigma} c_j^{(1-\sigma)\epsilon_g}$$

- Plugging this into the expenditure function immediately yields

$$e_j = \left[\sum_{g=1}^{G} \Omega_g \left[q_g c_j^{\epsilon_g} \right]^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

- Plugging (36) into (35), we get

$$u'(c_j) = \lambda_2 \sum_{g=1}^{G} \epsilon_g \cdot \frac{q_g c_{jg}}{c_j} = \lambda_2 \cdot \frac{e_j}{c_j} \cdot \sum_{g=1}^{G} \epsilon_g \cdot \underbrace{\frac{q_g c_{jg}}{e_j}}_{=s_g} = \lambda_2 \cdot \frac{e_j}{c_j} \cdot \sum_{g=1}^{G} \epsilon_g s_g$$

- Together with (37), this yields the intertemporal equation

$$u'(c_j) \cdot \frac{c_j}{\bar{\epsilon} e_j} = \beta E \left[V_a(\chi^+) | \chi \right] \quad \text{with } \bar{\epsilon} = \sum_{g=1}^{G} \epsilon_g s_g.$$

- The Envelope theorem tells us that

Finally, the solution to the non-homothetic CES life-cycle model is given by the following equations:

  - Intertemporal allocation:

$$c_{jg} = \Omega_g \cdot \left[\frac{q_g}{e_j} \right]^{-\sigma} c_j^{(1-\sigma)\epsilon_g} \quad \text{and} \quad e_j = \left[\sum_{g=1}^{G} \Omega_g \left[q_g c_j^{\epsilon_g} \right]^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

  - Euler equation:

$$u'(c_j) \cdot \frac{c_j}{\bar{\epsilon} e_j} = \beta (1 + r^+) E \left[u'(c_j^+) \cdot \frac{c_j^+}{\bar{\epsilon}^+ e_j^+} \middle| \chi \right]$$

  - Expenditure share and average elasticity:

$$s_g = \frac{q_g c_{jg}}{e_j} \quad \text{and} \quad \bar{\epsilon} = \sum_{g=1}^{G} \epsilon_g \cdot s_g$$

Some restrictions have to be taken into account w.r.t. the parameter choices. Let $\epsilon_{\min} = \min\{\epsilon_g\}_{g=1}^{G}$ and $\epsilon_{\max} = \max\{\epsilon_g\}_{g=1}^{G}$. Then the parameter γ is restricted to

$$\frac{1}{\gamma} > \begin{cases} 1 - \epsilon_{\min} & \text{if } 0 < \sigma < 1 \\ 1 - \epsilon_{\min} \left[1 - \frac{1}{4}(\sigma - 1) \left(\frac{\epsilon_{\max}}{\epsilon_{\min}} - 1 \right)^2 \right] & \text{if } \sigma > 1 \end{cases}$$

E.2 Market equilibrium

To be added

E.3 Stationary solution

To be added

...

F Model: Decomposition of correlation structure

Table F.8: Correlation coefficients in Austria

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.581	0.933	0.564		
Model version:						
1	(Basic life-cycle model)	0.580	1.000	0.580		
2	(+ non-homotheticity)	0.581	1.000	0.579		
3	(+ taste shifters)	0.580	0.984	0.570		
Final	(+ footprint shifters)	0.580	0.935	0.541		

Table F.9: Correlation coefficients in Czechia

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.753	0.832	0.615		
Model version:						
1	(Basic life-cycle model)	0.755	1.000	0.755		
2	(+ non-homotheticity)	0.751	0.994	0.738		
3	(+ taste shifters)	0.751	0.940	0.698		
Final	(+ footprint shifters)	0.751	0.910	0.676		

Table F.10: Correlation coefficients in Germany

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.728	0.963	0.716		
Model version:						
1	(Basic life-cycle model)	0.732	1.000	0.732		
2	(+ non-homotheticity)	0.728	1.000	0.727		
3	(+ taste shifters)	0.728	0.991	0.720		
Final	(+ footprint shifters)	0.728	0.981	0.714		

Table F.11: Correlation coefficients in Spain

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.655	0.964	0.626		
Model version:						
1	(Basic life-cycle model)	0.659	1.000	0.659		
2	(+ non-homotheticity)	0.656	1.000	0.655		
3	(+ taste shifters)	0.656	0.982	0.644		
Final	(+ footprint shifters)	0.656	0.959	0.629		

Table F.12: Correlation coefficients in Greece

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.568	0.938	0.543		
Model version:						
1	(Basic life-cycle model)	0.570	1.000	0.570		
2	(+ non-homotheticity)	0.567	1.000	0.566		
3	(+ taste shifters)	0.567	0.995	0.564		
Final	(+ footprint shifters)	0.567	0.937	0.530		

Table F.13: Correlation coefficients in Sweden

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.599	0.907	0.549		
Model version:						
1	(Basic life-cycle model)	0.603	1.000	0.603		
2	(+ non-homotheticity)	0.600	1.000	0.601		
3	(+ taste shifters)	0.599	0.972	0.584		
Final	(+ footprint shifters)	0.599	0.928	0.557		

Table F.14: Correlation coefficients in Slovakia

		Correlation coefficient			R^2	
		Con_Inc	Con_Em	Inc_Em	Con	Inc
Data		0.664	0.937	0.623		
Model version:						
1	(Basic life-cycle model)	0.679	1.000	0.679		
2	(+ non-homotheticity)	0.670	1.000	0.669		
3	(+ taste shifters)	0.669	0.993	0.664		
Final	(+ footprint shifters)	0.669	0.921	0.616		

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

Table G.15: 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 G.15 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 Services**	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 G.15 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 G.15 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 G.15 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.