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

Nicole Berr
University of Regensburg

Fabian Kindermann
University of Regensburg, CEPR, HCEO, and Netspar

Julia Le Blanc
European Commission, Joint Research Centre, and CEPR

June 25, 2026

Preliminary and incomplete

Abstract

Household net income is only a weak predictor of carbon footprints in the cross-section. We document this fact using a harmonized dataset linking environmentally extended supply-use tables to the European Household Budget Survey across 26 EU countries, in which emissions inequality is driven primarily by within-country variation. To recover the lifetime income-emissions relationship, we calibrate an overlapping-generations model with non-homothetic CES preferences, where households allocate consumption across five categories with distinct emissions intensities. Identification comes from the non-proportional consumption-income relationship, heterogeneity in consumption baskets, and variation in emissions intensities across goods. The calibrated model delivers the first quantification of the lifetime income-emissions relationship for EU households. Life-cycle consumption dynamics account for a substantial share of the attenuated cross-sectional gradient, implying that standard cross-sectional analyses significantly overstate the regressivity of carbon pricing.

JEL Classification: Q52, D15, D31, E21
Keywords: greenhouse gas emissions, inequality, life cycle, carbon footprint

Contact Information:
nicole.berr@ur.de, fabian.kindermann@ur.de, julia.le-blanc@ec.europa.eu

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. A key methodological challenge in evaluating the distributional consequences of carbon pricing lies in distinguishing between current and lifetime economic resources. Most existing empirical evidence analyzes carbon footprints and the incidence of carbon taxation using cross-sectional data. In such data, current income is an imperfect proxy for consumption, as households smooth their consumption over the life cycle. Consequently, the observed relationship between current income and emissions may substantially understate the underlying relationship between lifetime economic resources and carbon footprints. Whether carbon pricing appears regressive therefore depends crucially on the incidence concept - current versus lifetime resources - employed in the analysis. We show that this distinction matters quantitatively. While the elasticity of emissions with respect to current income is only around 0.5 - 0.6 in the cross section, the corresponding elasticity with respect to lifetime resources is substantially higher and close to proportional. Moreover, using simulated lifecycle data, we show that a substantial fraction of emissions inequality reflects variation within households over the lifecycle rather than persistent differences across households.

To study these questions, we develop a detailed and harmonized micro dataset of household greenhouse gas (GHG) emissions covering all 27 member states of the European Union.[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.

[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.

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. 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). The resulting dataset covers more than 270,000 households and allows us to consistently measure both direct and indirect consumption-related greenhouse gas emissions across the European Union. This comprehensive dataset enables us to explore the dimensions of both between- and within-country inequality in household carbon footprints within the EU.

Our empirical analysis yields three key findings. First, household carbon footprints are highly concentrated in a small number of consumption categories, most notably food, housing (incl. housing energy), and transportation. Second, within-country variation in households' carbon footprints is an order of magnitude greater than cross-country variation. Third, current household income is only a weak predictor of household carbon footprints. While emissions increase with income, the estimated elasticity of emissions with respect to current income is well below one and income explains only a limited share of the observed variation in emissions. Total consumption is a substantially stronger predictor of emissions, indicating that the weak income-emissions relationship primarily reflects the nonlinear mapping from income to consumption. Nevertheless, considerable residual heterogeneity remains because households differ in both expenditure composition and emission intensities.

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, heterogeneity in emission intensities, and the distinction between transitory and permanent components of emissions inequality.

To address these challenges, 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 heterogeneity capture residual heterogeneity within consump-

tion groups. The model is explicitly designed to replicate the key patterns documented in the data. Together, these mechanisms reconcile the weak relationship observed in cross-sectional data with the much stronger relationship that emerges from a lifetime perspective.

A central insight of our analysis is that the weak cross-sectional relationship between income and emissions does not reflect the underlying structural link between economic resources and carbon footprints. Instead, it is largely driven by life-cycle dynamics and transitory income fluctuations. When households are tracked over their entire life cycle and lifetime resources are taken into account, inequality in lifetime income is strongly associated with inequality in lifetime emissions, with a relationship close to proportional. While the elasticity of emissions with respect to current income is only around 0.5 - 0.6 in the cross section, the corresponding lifetime elasticity rises to approximately 0.9 when households are evaluated using present-value lifetime resources. This implies that carbon footprints are much more closely aligned with lifetime income than cross-sectional data suggest. At the same time, the model shows that a substantial fraction of observed carbon inequality reflects lifecycle variation within households rather than persistent differences across households.

These findings highlight the importance of adopting a dynamic perspective when analyzing the distributional effects of carbon pricing. Policies based solely on current income may mischaracterize the distribution of carbon burdens, as they fail to account for the underlying distribution of lifetime resources. At the same time, differences in consumption composition remain relevant, as emission intensities vary across consumption categories and along the income distribution. Consequently, evaluations of carbon pricing based exclusively on current income may provide an incomplete picture of distributional incidence. While cross-sectional measures remain relevant for short-run distributional outcomes and political acceptance, they do not necessarily capture differences in permanent economic resources. A lifetime perspective therefore complements standard incidence analyses and helps distinguish between temporary and persistent sources of carbon inequality. This distinction is particularly relevant for assessing the distributional consequences of carbon pricing, since policies may appear less regressive when evaluated relative to households' lifetime resources.

Our paper is organized as follows. After a brief review of the literature, Section 2 describes the data sets used and the matching procedure between aggregate emissions data and household-level consumption data. In Section 3, we provide a set of stylized facts of cross-country and within-country inequality of carbon footprints. Section 3.2 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.

An emerging literature studies the distributional consequences of carbon pricing from a dynamic and life-cycle perspective. Early contributions such as Hassett et al. (2007) show that carbon taxes appear substantially less regressive when households are ranked by measures of lifetime rather than current income. More recent heterogeneous-agent climate models analyze how incomplete markets, non-homothetic preferences, and expenditure heterogeneity shape the incidence of climate policy across households and cohorts (Fried et al., 2018, 2024). Related recent work also studies the life-cycle incidence of carbon taxation in quantitative overlapping-generations frameworks with heterogeneous energy expenditure patterns (Barrell-Kane and Yazici, 2026).

At a broader level, a related literature examines the relationship between inequality and aggregate emissions. Although falling marginal propensities to emit suggest there may be a short-run trade-off between redistribution and emissions reductions, political-economy dynamics can instead produce the reverse association at a more structural level. Flechtner and Middelanis (2025) reconcile these perspectives by distinguishing within-country redistribution effects from cross-country structural inequality effects. Our paper complements this literature by focusing on the microeconomic relationship between income dynamics, consumption behavior, and household carbon footprints within EU countries.

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 representations of household heterogeneity. As a result, they are generally not designed to replicate the granular cross-sectional variation in income dynamics, expenditure composition, and household 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 new empirical evidence 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, the model provides a micro-founded explanation for the weak cross-sectional relationship between current income and household carbon footprints. At the same time, the model shows that this weak relationship masks a much stronger underlying link: when households are evaluated over their life cycle, lifetime income is closely aligned with lifetime carbon footprints.

2 A Micro Database of Household Carbon Emissions

Assembling a dataset on household level carbon footprints requires data on both the environmental impact of different goods and on the consumption expenditure of households, for which we employ two data sources. 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).[2] We use version 3 of the monetary EXIOBASE dataset, which originally contained time series data from 1995 to 2011 and was later extended up to the year 2022[3]. It covers 49 different regions consisting of 44 countries, including the 27 EU member states and 17 larger countries, as well as five ¨Rest of the World¨ (RoW) regions. Table A.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 F1 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.[4] 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.

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

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

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

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

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. 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[5] 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.

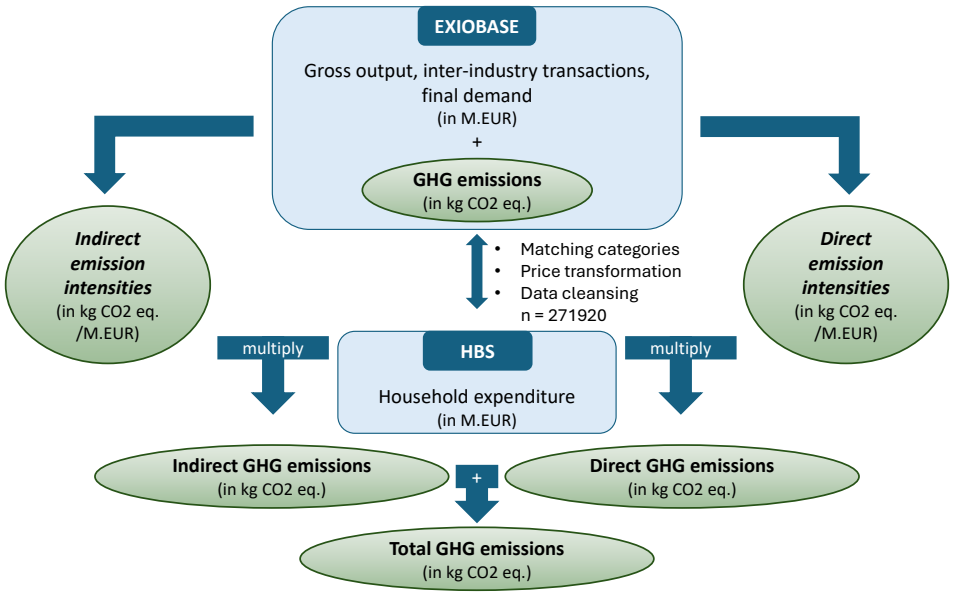
One goal of this study is to construct an internationally comparable dataset on the individual consumption footprint. There are a few studies that combine environmentally augmented input-output data with individual level consumption data to derive a measure of the individual carbon footprint, see Sager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

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

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.

A compact visualization of the matching procedure is displayed in Figure 1.

Figure 1: Matching procedure



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 F1.[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.

[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

3 Empirical Analysis

3.1 Stylized Facts

We start by documenting the key stylized facts of the distribution of greenhouse gas (GHG) emissions in our sample. In particular, our data suggest the following:

1. *Almost* 70% *of household carbon footprint is due to the consumption of food, housing (incl. housing energy) and transportation.*
2. *Carbon inequality between households is mostly due to within country inequality.*
3. *Household net income is a weak predictor of carbon footprints in the cross-section.*

We now discuss these stylized facts in detail.

3.1.1 Major Greenhouse Gas Emitters

Household-level greenhouse gas (GHG) emissions are closely linked to consumption behavior. Panel (a) of Figure 2 presents average expenditure shares for five broad consumption aggregates for the pooled sample of EU households, together with the contribution of the underlying subcategories.[8] The analysis focuses on the consumption groups that account for the largest share of household carbon footprints - Food, Housing Services, Housing Energy, and Transport - while all remaining goods are grouped into the residual category "Others". In expenditure terms, the largest components are food, housing services (including rents), and other goods and services.

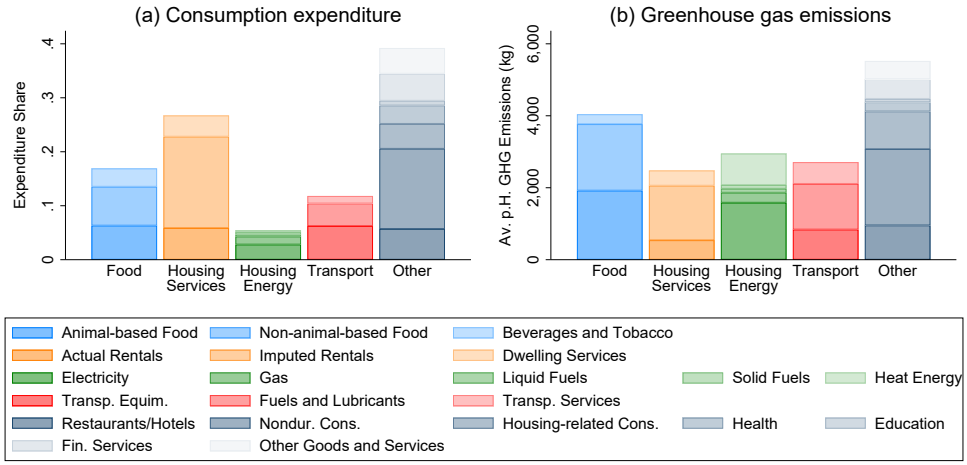
Panel (b) of Figure 2 shows the corresponding average GHG emissions (direct and indirect) associated with each consumption component.[9] On average, a typical EU household emits approximately 18 tons of greenhouse gases per year, measured in CO2-equivalents. In contrast to expenditure shares, housing energy and transportation (including fuels and lubricants, and transportation services) play a prominent role in these emissions. Food is also a major contributor to household carbon footprints. Overall, approximately 22 percent of the average household's carbon footprint is due to food consumption, 31 percent is related to housing services or housing energy, and 15 percent to transportation. Consequently, food, housing, and transport together account for about 70% of the household's carbon footprint.

gases like carbon dioxide, methane, nitrous oxide and sulphur hexafluoride to kilograms CO2-equivalents (kg CO2 eq.) according to Solomon et al. (2007).

[8] A detailed breakdown of all consumption categories and subcategories is provided in Tables A.1 and F1 in the appendix.

[9] The data behind this figure are shown in Table B1 in Appendix B.

Figure 2: 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. For Housing Services, emissions are only available at the aggregate category level. The subdivision shown is based on expenditure shares within Housing Services and serves illustrative purposes only.

A key insight from Figure 2 is the pronounced difference in the magnitudes of the expenditure shares and associated emissions. Certain consumption categories, such as housing services (e.g., rent), account for a large share of total expenditures but generate relatively limited 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. These differences highlight the importance of accounting not only for expenditure levels, but also for the carbon intensity of different consumption categories when analyzing household-level emissions.

3.1.2 Emissions Inequality between and within Countries

One 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. 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 $\mathcal{N}$.[10] Figure B1 in Appendix B shows the relationship between the Gini index and the $GE(1)$ index of household-level GHG emissions for each sample country. The two indices yield the same results, meaning that countries are ranked in the same order according to both indices. A simple linear regression between the two indices has an explained variance of $R^2 = 0.98$.

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

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

where $\omega_g = \frac{N_g}{N}$ is the relative size of population subgroup g, $\bar{F}_g$ is the average carbon footprint in subgroup g, and $GE_g(1)$ is the $GE(1)$ index for subgroup g. Consequently, the $GE(1)$ index can be broken down into two components. First, a within-group inequality component that is composed of the (weighted) inequality indices of household GHG emissions in each subgroup g. Second, a between-group component that measures differences in the average household footprint across different countries.

We exploit the decomposition property of the $GE(1)$ index to examine inequality in household carbon footprints within the entire EU. To this end, we calculate the total $GE(1)$ index, assuming that each country forms one subgroup. The results of this decomposition for total household GHG emissions, as well as selected consumption components, are shown in Table 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 subcomponents 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 number is about 9 percent. These results

[10] 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.

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.

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. In Section 3.2, we will investigate heterogeneity in household consumption baskets within countries more thoroughly.

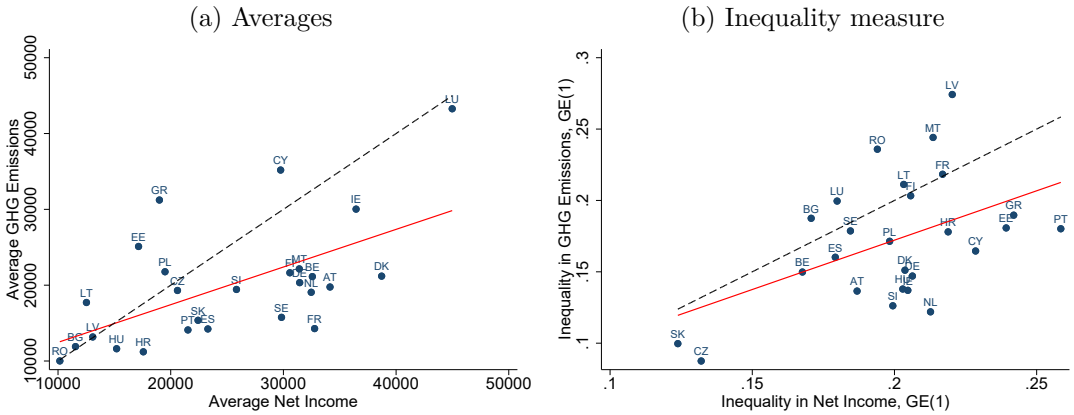
3.1.3 Relation Between Net Income and Emissions

To shed more light on the link between income and household carbon footprints, Figure 3 shows cross-country scatter plots of average net income and average household GHG emissions (Panel a) and income inequality and emissions inequality (Panel b). The red lines indicate a simple linear regression line, while the dashed lines show the 45-degree line as a reference point.

Both plots generally show a positive association between incomes and emissions, as evident from the slope of the regression lines. This means that countries with higher average incomes tend to exhibit higher household GHG emissions, and countries with more income inequality tend to have higher inequality in household carbon footprints.[11] However, the relationship is relatively weak, as measured by the explanatory power of the simple regressions. A linear regression can only

[11]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 B2 in Appendix C.

Figure 3: 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.

explain 34 percent of the variance in average GHG emissions across countries and only 22 percent of the variance in inequality.[12] Overall, the cross-country evidence suggests that a substantial share of variation in household-level carbon footprints cannot be accounted for by differences in income alone.

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 B3 in the appendix, 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 to a large extent shaped by the structure of consumption baskets and the emissions intensity of different consumption components and not by consumption or income levels.

As a next 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

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

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

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

The results in Table 2 confirm that the within-country relationship between income and emissions is both positive and strongly non-linear. Higher-order income terms are highly statistically significant and improve the fit of the regression specification, as measured by the R^2 value. However, despite this non-linearity, income remains a relatively weak predictor of household carbon footprints. 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".[13] 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 only at about 32%, 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 corresponding regressions using household consumption instead of income are reported in Table B2 in the appendix. Consistent with the idea that emissions are more directly linked to consumption than to current income, the explanatory power increases when consumption is used as the explanatory variable. Nevertheless, even conditional on total consumption expenditure, a considerable share of variation in household carbon footprints remains unexplained. Table B3 further shows that augmenting the regressions with additional household characteristics - including age, household size, education, homeownership, and population density - only marginally increases explanatory power. Our findings suggest that, similar

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

to the cross-country setting, income is not a strong predictor of household carbon emissions within a country. Substantial heterogeneity in household carbon footprints persists even after conditioning on income, consumption, and observable household characteristics.

Table 3 provides additional evidence on the joint distribution of income, consumption, and emissions after controlling for country fixed effects.

Table 3: Coefficients of variation and correlation of income, consumption and emissions

Coefficients of Variation	Income	Consumption	Emissions
	0.635	0.521	0.562
Correlation Coefficients	Inc_Con	Con_Em	Inc_Em
	0.638	0.846	0.551

Consumption is substantially less dispersed than income, consistent with households smoothing consumption over the life cycle. Emissions exhibit an intermediate level of dispersion, with an estimated coefficient of variation (CV) of 0.56. The correlation between income and consumption is only moderate with a pairwise correlation coefficient of 0.638, indicating that current income explains only part of the variation in household consumption. By contrast, the correlation between consumption and emissions is substantially stronger, though still clearly below one. Consequently, the correlation between income and emissions is even weaker, with a correlation coefficient of 0.551. This suggests that household carbon footprints are shaped both by the dynamic relationship between income and consumption and by heterogeneity in expenditure composition and emission intensities.

To sum up this section, our empirical analysis has delivered several important insights into household carbon inequality in the EU. A large share of household carbon footprints is concentrated in a small number of consumption categories, most notably food, housing (including housing energy), and transportation. At the same time, the majority of inequality in household-level GHG emissions arises within rather than between countries. Moreover, both the cross-country and within-country relationship between income and emissions are relatively weak, implying that households with similar incomes can exhibit substantially different carbon footprints. These findings raise the question of which mechanisms generate the observed heterogeneity in household carbon emissions beyond differences in income alone. In particular, the weak relationship between income and emissions in the cross-section suggests that the dynamic relationship between income and consumption, differences in expenditure composition, and heterogeneity in emission intensities may all play an important role. In the following section, we therefore decompose the relationship between income, consumption, and emissions into its main components and examine how each contributes to the observed distribution of household carbon footprints.

3.2 Towards understanding the income-emissions relationship

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

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

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. The empirical analysis in the previous section further indicated that these mechanisms may be quantitatively important for understanding why household income is only weakly related to carbon footprints in the cross-section. To better understand the mechanisms underlying the relationship between income and emissions, we now examine the individual components of equation 1 in more detail and formulate a set of empirical features that discipline the quantitative model developed in the following section. Specifically, we analyze how each decomposition component varies with income and consumption and how it contributes to the overall income, consumption and emissions relationship.

Feature 1. *The relationship between income and consumption is strongly non-proportional.*

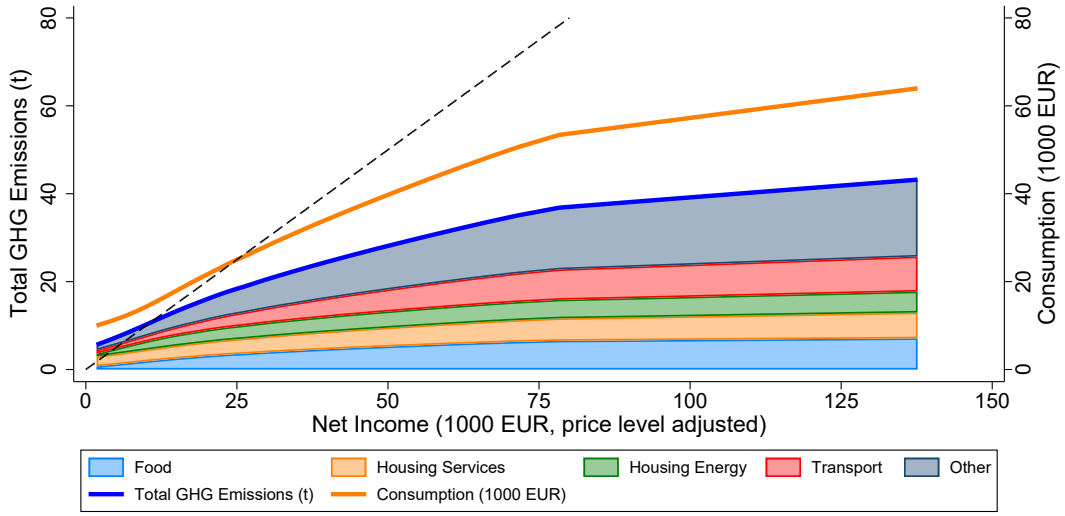
Figure 4 documents this feature by illustrating the relationship between consumption, income, and emissions across the income distribution. To construct this figure, we proceed as follows: We divide all sample households into percentile groups p according to their price-level-adjusted net household income. We then run regressions of the following form:

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

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.[14]

Figure 4: The within-country relation between income and consumption



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 B4 in Appendix B.

The dashed line in Figure 4 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 B2 in the appendix. The insights from this part of the analysis are formalized as feature 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.

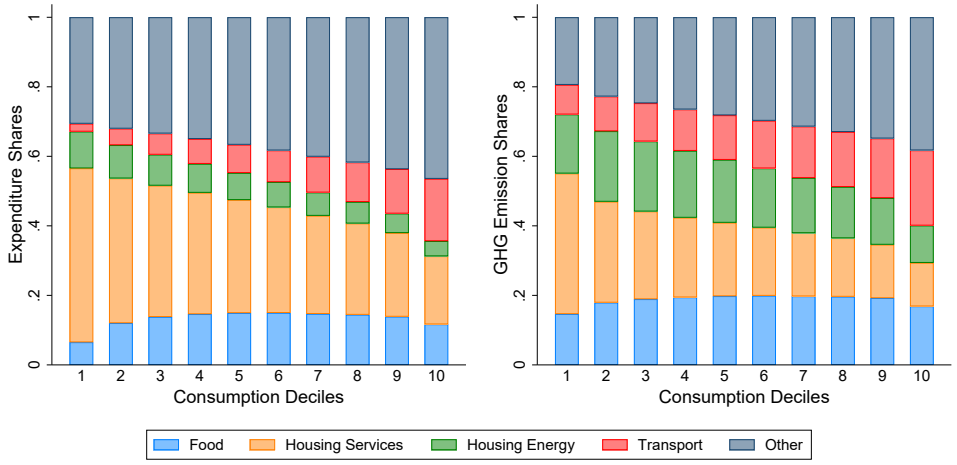
Feature 2. *Consumption baskets vary systematically across consumption levels.*

We next examine the composition of the consumption basket along the consumption distribution, corresponding to the second component of equation (1). Figure

[14]The unsmoothed data is shown in Figure B4 in Appendix B.

5 displays expenditure shares and corresponding emission shares across consumption deciles. To calculate this figure, we use the same regression specification as in equation (2), but with deciles of the consumption distribution instead of the income distribution.

Figure 5: Consumption basket and emission composition over consumption



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 noticeable differences remain in the emission shares across consumption deciles. These differences are particularly pronounced for housing energy and other goods and services and suggest that households differ not only in how much they consume, but also in the carbon intensity of the goods they purchase. Taken together, these results indicate that household carbon footprints are shaped not only by total consumption levels, but also by systematic differences in expenditure composition across the distribution.

Feature 3. *There is substantial heterogeneity in consumption baskets even among households with similar overall levels of consumption.*

While Figure 5 documents systematic variation across consumption deciles, substantial heterogeneity also exists among households with similar overall consumption levels. Table 4 shows the coefficients of variation in the single consumption components and their associated carbon 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.

Table 4: 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

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. 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).

Feature 4. *Carbon intensities vary substantially even conditional on similar consumption patterns.*

Even after controlling for the household's consumption level, substantial heterogeneity in carbon footprints across households remains. Figure 5 emphasizes the importance of this variation for different deciles of the consumption distribution. Table 4 shows that 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 additional 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. Overall, these findings suggest that variation in consumption patterns alone is insufficient to account for the observed heterogeneity in household carbon footprints. Additional heterogeneity in the carbon intensity of consumption goods appears to play an important quantitative role.

3.3 Summary of Empirical Analysis

In summary, our analysis indicates that household-level carbon emissions are driven by several distinct mechanisms and that a model of the household carbon footprint should have the following four features:

1. *The relationship between income and consumption is strongly non-proportional, hence we need to model a nonlinear link between the two.*

2. *Consumption baskets vary systematically across consumption levels, hence we need to capture changing consumption baskets across consumption deciles.*

3. *There is substantial heterogeneity in consumption baskets even among households with similar overall levels of consumption, so we need to account for variation in consumption baskets within each consumption decile.*

4. *Carbon intensities vary substantially even conditional on similar consumption patterns, therefore we need to account for additional heterogeneity in emission intensities.*

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 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 features established in Section 3.2. We explicitly incorporate the substantial heterogeneity across EU member states documented in Section 3. Section 3.1.2 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 3.2. Wealth accumulation plays a

[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.

central role in the model, as it permits households to shift consumption - and hence carbon emissions - across time. This capability of the model is essential for the comparative analysis of cross-sectional and life-cycle carbon inequality. 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 feature 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 4 in Section 3.2 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 observed 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

[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.

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 feature 1.

Households consume different goods c_{jg} at prices p_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 feature 2. To model these differences, there are two main approaches in the literature. The first approach is to use Stone-Geary 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 feature 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 such that retirees get a pension payment of $y = w\kappa_{ret} \exp(\eta_{j_r-1})$. 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 working household reads

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

4.1.2 Taste Heterogeneity

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 feature 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

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

Each good 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, this taste heterogeneity 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 Heterogeneity

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 Heterogeneity In Section 3.2 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, as formalized in feature 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 feature 4.

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

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

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

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

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

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

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

The solution to this non-homothetic CES life-cycle model is derived in Section C.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

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

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 $\bar{\epsilon} = \sum_{g=1}^{G} \epsilon_g \cdot s_g$ is the average elasticity and $s_g = \frac{p_g c_{jg}}{e_j}$ 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 and labor L to produce good Y according to the Cobb-Douglas production function

$$Y = \zeta K^{\alpha} L^{1-\alpha},$$

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. It sells its output Y on the goods market at the constant producer price $q = 1$ 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

$$\max_{K,L} \ \pi = \zeta K^{\alpha} L^{1-\alpha} - (r + \delta)K - w\, L.$$

This leads to the following first-order conditions:

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

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

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

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

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

4.3 Capital Markets, Trade and Equilibrium

This section presents the market structure, which is kept as simple as possible while simultaneously allowing for differences in consumer prices of the G goods. 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

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

where A are the country's aggregate private savings and Q is the country's net foreign asset position. When $A < K$ such that $Q < 0$, 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 $\bar{r}Q$, implying a trade balance of

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

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

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

where C denotes the country's private consumption, I its investment and TB the trade balance. We assume that government expenditure G 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. As a result, households in each country face different consumer prices p_g.

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

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. Table D1 in the appendix presents a structured overview of the model parameters together with the corresponding calibration strategy.

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 a common level of 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

Finally, we 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 this by allowing for differences in the parameters of the income process $(Var(\log y)^c, \sigma_\epsilon^2, \sigma_\nu^2)$, pension age (J_r^c), and the earnings process (κ_j^c). To model the respective changes in the consumption basket, we calibrate the parameters of the non-homothetic preferences $(\bar{\Omega}_g^c, \epsilon_g^c)$ for each country. Finally, the taste heterogeneity (ω_g^c) in equation (6) as well as average emission intensities $(\bar{\Phi}_g^c)$ and footprint shifters (ϕ_g^c) in (8) vary by country. Importantly, households in each country also face different consumer prices p_g^c.

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 4. 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 $\varepsilon^+ \sim N\big(0,\ \sigma_\eta^2\big)$, 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

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

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 $\mathrm{Var}(\log y)^c$ 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,

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

We choose σ_ε^2 and σ_ν^2 such that

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

This implies

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

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

[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.

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 p_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 heterogeneity ϕ_g^c is 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 4.

5.3 Model Fit and Mechanisms

In this section, we present simulation results from our calibrated model. We start by assessing whether the model can replicate the key empirical facts documented in Section 3. After establishing that the model provides an adequate overall fit, we then turn to understanding how the model achieves this fit. Specifically, we systematically decompose the contribution of each model component, quantifying its effect on the implied correlation structure among income, consumption, and emissions and on key patterns observed in the data.

5.3.1 Replication of Cross-Sectional Patterns

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 6. The nonlinear relationship between income and consumption across countries is depicted in Figure 7. For this figure, we build on Figure 4 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 reproduces the empirical relationship closely for the majority of countries, with only a small number of notable deviations.

Figure 6: The correlation between income and consumption across countries

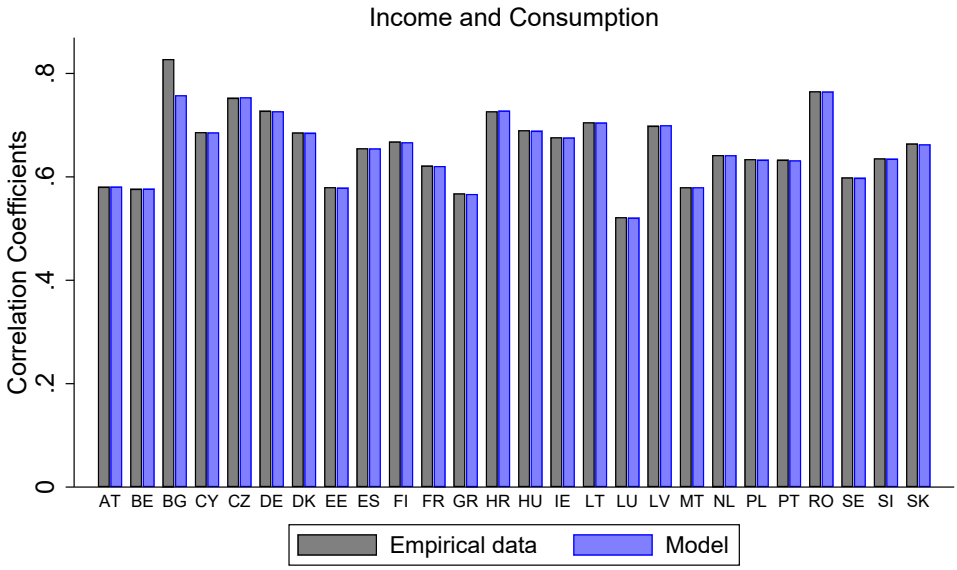
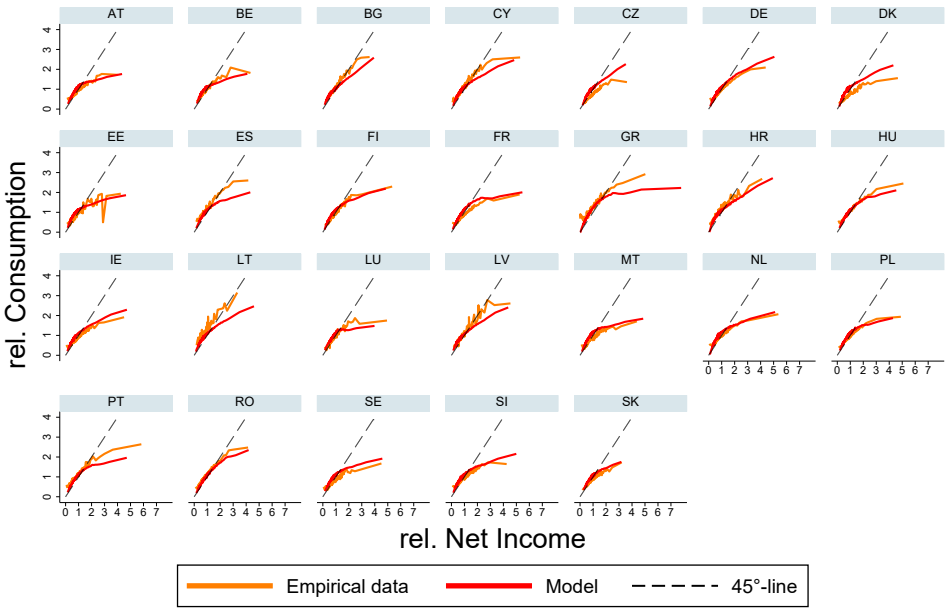


Figure 7: The relation between income and consumption across countries

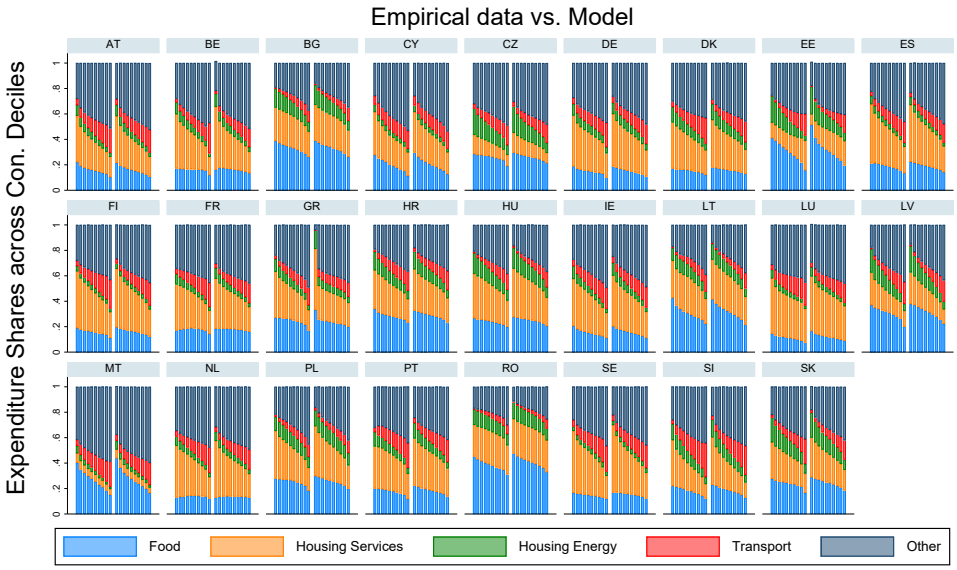


Explanations: All variables were scaled by average total household monetary net income of the respective country.

The model's performance in matching the cross-country composition of the consumption basket is presented in Figure 8, 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.

Figure 8: Country-specific expenditure shares across consumption deciles



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 D2 in Appendix D.2 reports the within-decile variation in consumption and emissions implied by the model. The model closely matches these calibration targets across countries. Detailed country-specific results 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.

5.3.2 Mechanisms Behind the Income-Emissions Relationship

In the following section, we investigate which mechanisms are responsible for the weak empirical relationship between income and household carbon emissions. To this end, we sequentially introduce the different model components and examine how they affect the correlation structure implied by the model. The decomposition distinguishes between mechanisms that alter the mapping from current income to current consumption through income risk and consumption smoothing, and mechanisms that alter the mapping from consumption to emissions through expenditure composition and carbon intensities.

Table 5 reports, for the illustrative case of France, the pairwise correlation coefficients between consumption, income, and emissions, together with 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 entire life cycle. Formally, this

Table 5: 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)	0.981	1.000	0.981	1.000	0.962
2 (+ persistent income risk)	0.874	1.000	0.874	1.000	0.767
3 (+ iid income shock)	0.632	1.000	0.632	1.000	0.399
4 (+ non-homotheticity)	0.621	0.998	0.622	0.996	0.387
5 (+ taste heterogeneity)	0.621	0.960	0.598	0.922	0.358
6 (+ footprint heterogeneity)	0.621	0.808	0.503	0.653	0.253

corresponds to an identity transition matrix and the absence of transitory income shocks. Since all income heterogeneity is deterministic and persistent, current income closely tracks lifetime resources, implying that consumption closely follows income and emissions are almost perfectly tied to consumption.

Introducing persistent income transitions and subsequently transitory income shocks induces precautionary saving and consumption smoothing, substantially weakening the contemporaneous relationship between current income and current consumption. Non-homothetic preferences then weaken the link between consumption and emissions by allowing expenditure shares to vary systematically with the level of consumption. Taste heterogeneity introduces persistent differences in consumption baskets even among households with similar resources. It captures structural differences in lifestyles, local environments, and consumption opportunities that are not fully explained by income alone. While its primary role is to match the observed dispersion in expenditure patterns within consumption groups, it also further weakens the relationship between consumption and emissions. Finally, footprint heterogeneity introduces persistent variation in the carbon intensity of consumption conditional on expenditure. It captures differences in product quality, production technologies, energy sources, and local infrastructure, implying that households with similar expenditure patterns may nevertheless face systematically different carbon exposure. This final component is essential for reproducing the empirical correlation between consumption and emissions.

Taken together, the decomposition shows that income risk and life-cycle dynamics primarily affect the mapping from current income to current consumption, whereas non-homotheticity, taste heterogeneity, and footprint heterogeneity determine how consumption translates into emissions. The full model is therefore required to reproduce the joint correlation structure observed in the data.

A detailed version of this decomposition for all countries is provided in Appendix D.3.

6 A Lifecycle Assessment of the Individual Carbon Footprint

Having validated the model calibration, we now use the structural framework to study the relationship between income, consumption, and emissions from a lifetime perspective. In particular, we compare cross-sectional and lifetime measures of carbon inequality and examine how life-cycle dynamics, consumption smoothing, non-homothetic preferences, and heterogeneity in consumption patterns shape the relationship between economic resources and household carbon footprints over the life cycle. We begin by verifying that the model can replicate the within-country cross-sectional relationships documented in Section 3.2. Specifically, we simulate a large panel of $N = 1{,}000{,}000$ households per country over the life cycle using the model-implied policy functions and stochastic income processes.[18] Applying the same percentile-based regression approach as in Figure 4 yields the results reported in Appendix Figure E1.

The model closely reproduces the key empirical patterns. Consumption rises less than proportionally with current income, reflecting life-cycle consumption smoothing, while emissions closely track consumption. Overall, these findings confirm that the model captures the key mechanisms underlying the attenuated cross-sectional relationship between income and emissions. In addition, the model also reproduces the observed age profiles of income, consumption, and emissions across countries. Appendix Figure E2 compares the corresponding empirical and simulated life-cycle profiles and shows a close fit for the majority of countries.

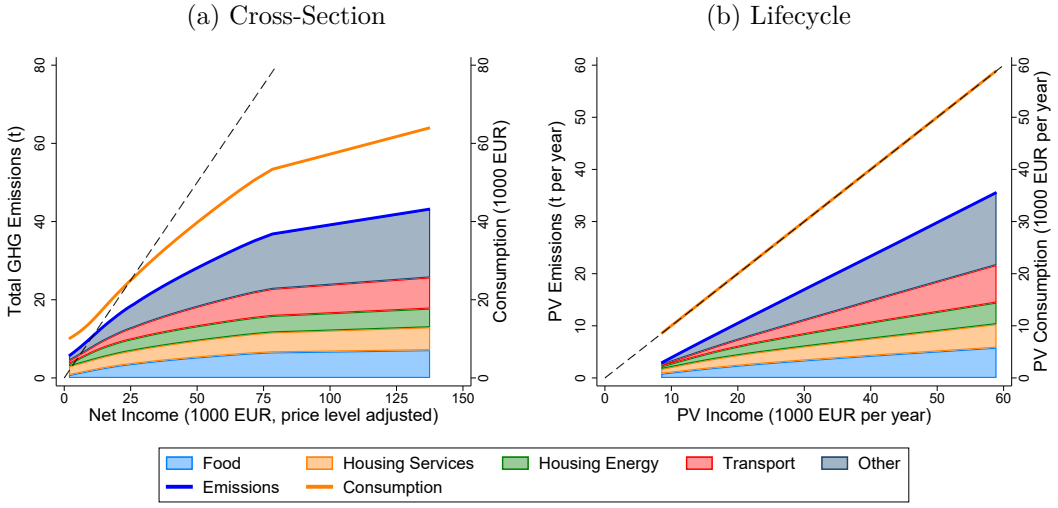
While the model successfully replicates these cross-sectional patterns, such comparisons are inherently affected by transitory income fluctuations and life-cycle dynamics. The structural framework of our model allows us to go beyond this limitation by tracking households over their entire life cycle and focusing on lifetime resources. This approach allows us to analyze the joint distribution of lifetime resources and lifetime carbon footprints within a unified structural framework. Importantly, the cross-sectional and lifetime perspectives address different economic questions. Cross-sectional measures are informative about short-run exposure to carbon pricing and therefore remain highly relevant for liquidity constraints, transition dynamics, and policy considerations. The lifetime perspective, by contrast, isolates persistent differences the economic resources of the households from transitory income fluctuations and life-cycle timing effects. The objective of the lifetime analysis is therefore not to replace the cross-sectional perspective, but to complement it by characterizing the long-run relationship between permanent resources and carbon footprints.

To this end, we construct present-value (PV) measures of lifetime outcomes at the household level. For each simulated household, we first compute the present values of income (including both labor and asset income), consumption expenditure,

[18] For computational tractability, we construct the percentile profiles based on a subsample of 10,000 households per country.

and associated GHG emissions by discounting future flows at the model-implied interest rate. The present values of lifetime income, consumption expenditure, and associated emissions are then obtained by aggregating these discounted flows over the life cycle. Finally, we use the PV lifetime aggregates to construct annualized present-value measures of labor income, consumption, and emissions. This transformation expresses all variables as constant yearly equivalents over the life cycle and removes the effects of intertemporal consumption smoothing. We focus on labor income in this representation, as it captures the exogenous component of lifetime resources in the model. While total income also includes asset income, the latter is endogenously determined through saving behavior and therefore reflects intertemporal choices rather than underlying earning capacity. Using labor income isolates the underlying income process that shapes lifetime resources and thus provides a cleaner measure of permanent resources that drive consumption and, in turn, emissions. Panel (a) of Figure 9 reproduces the empirical cross-sectional relationship and Panel (b) shows the outcomes obtained when we redo the analysis using annualized present-value metrics for labor income, consumption, and emissions.

Figure 9: The within-country relation between income, consumption, and emissions: cross-section vs. lifecycle



Explanations: Panel (b) shows own calculations based on simulated life-cycle data. The figure is based on a subsample of 10,000 households per country drawn from the full simulated sample of 1,000,000 households per country. This figure presents the annualized equivalents of the corresponding discounted lifetime present values, that is, constant yearly flows yielding the same present value over the life cycle.

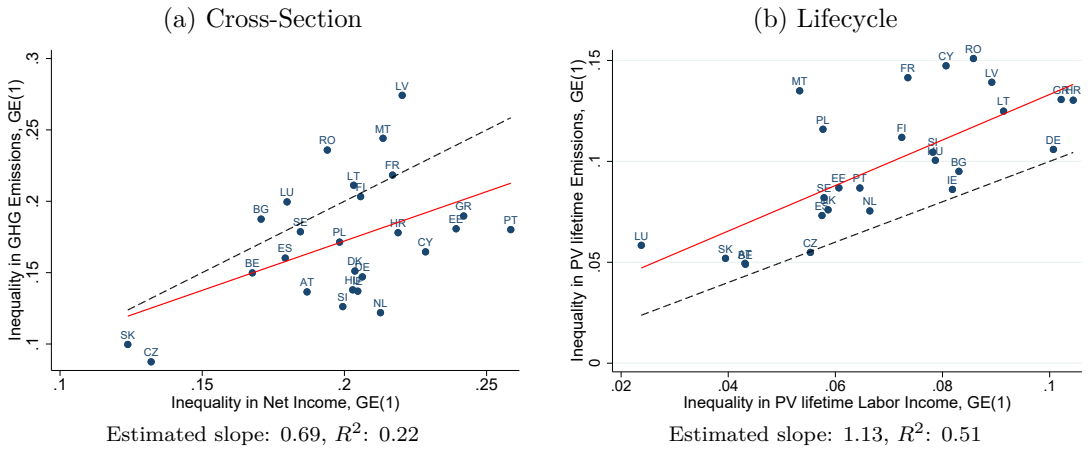
Two key differences emerge. First, consumption closely aligns with labor income and lies almost exactly on the 45-degree line. This reflects the lifetime budget constraint: when expressed in annualized present-value terms, consumption is effectively pinned down by lifetime resources, eliminating most of the non-linearity observed in the cross-section. Second, emissions continue to closely track consumption, but the relationship remains below perfect proportionality. This in-

dicates that persistent heterogeneity in consumption composition and emission intensities remains quantitatively important even after abstracting from life-cycle dynamics. The corresponding PV emissions per Euro of household spending are reported in Appendix Figure E3.

Taken together, these results show that the weak relationship between income and emissions in the cross-section is to a substantial extent driven by the non-linear mapping from income to consumption over the life cycle. Once lifetime resources are considered, this non-linearity largely disappears, and the relationship between economic resources and emissions becomes substantially tighter. Nevertheless, the relationship does not become one-to-one, as persistent differences in consumption baskets and in emission intensities continue to generate meaningful dispersion in lifetime emissions conditional on lifetime resources.

Figure 10 compares the relationship between inequality in income and emissions in the cross-section and over the life cycle. Panel (a) reproduces the empirical cross-sectional relationship between income inequality and emission inequality from Figure 3. Panel (b) presents the corresponding relationship using simulated present-value lifetime measures of labor income and emissions.

Figure 10: Correlation of inequality emissions and income: cross-section vs. lifecycle



Explanations: Calculations for Panel (b) are based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. We derive discounted present values and compute aggregate lifetime totals from the resulting flows.

The comparison reveals that there is a much tighter relationship between inequality in income and emissions when households are evaluated from a lifetime perspective. Inequality in present-value lifetime income is strongly positively associated with inequality in lifetime emissions, with substantially higher explanatory power than in the cross-section. This indicates that a large share of the variation in lifetime carbon footprints can be attributed to differences in lifetime resources. The mechanism underlying this result is illustrated more directly in Appendix Figure E4, which decomposes the relationship between lifetime income, consumption,

and emissions. Households smooth consumption over time in response to transitory income fluctuations and life-cycle dynamics, implying that current income is only an imperfect measure of underlying economic resources in the cross-section. By contrast, PV lifetime labor income closely tracks lifetime consumption possibilities through the intertemporal budget constraint. Since emissions are directly linked to consumption decisions, this translates into a substantially stronger association between lifetime income inequality and lifetime emissions inequality.

To complement the graphical analysis, we formally quantify the strength of the relationship between income and emissions using simple regression models. Table 6 compares the empirical cross-sectional relationship between income and emissions with the corresponding relationship obtained from PV lifetime measures in the model. The empirical specification follows the baseline regression presented in Table 2 in Section 3.2. The simulated cross-sectional estimates are obtained by applying the same specification to the model-generated cross section, while the final column reports estimates based on PV lifetime income and lifetime emissions.[19]

Table 6: The simulated cross-sectional vs. lifetime relation between income and emissions

	Empirical Cross-Section	**Simulated Cross-Section**	**Simulated Lifetime PV**
Income in €	0.324***	0.318***	0.543***
	(0.00628)	(0.000266)	(0.00138)
Country FE	yes	yes	yes
N	256,299	15,860,000	260,000
R^2	0.415	0.480	0.711
R^2 explained by income	0.283	0.336	0.595
Mean income in €	26,835.6	26,904.2	793,737.9
Mean emissions in kg	17,762.9	17,777.3	472,647.6
Elasticity at mean	0.490	0.482	0.911

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

Explanations: Column (1) reports the empirical cross-sectional relationship between household income and greenhouse gas emissions. Column (2) reports the corresponding relationship obtained from simulated cross-sectional data. Column (3) reports estimates based on present-value lifetime income and lifetime emissions. Simulated results are based on a random subsample of 10,000 households per country drawn from a simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

The empirical cross-sectional estimates in Table 6 confirm that household carbon footprints increase less than proportionally with income. Depending on the specification, the estimated empirical elasticity of emissions with respect to income is approximately 0.49, implying that a 1% increase in income is associated with only a 0.49% increase in emissions. This magnitude is broadly consistent with the

[19]More flexible specifications including quadratic and cubic income terms are reported in Appendix Table E7, summarizing individual Tables E1 and E8.

existing household carbon footprint literature. Survey evidence summarized by Pottier (2021) shows that estimated income elasticities of household carbon footprints are typically well below one and often range between approximately 0.3 and 0.8, depending on the country, time period, and emissions concept considered.

The model successfully reproduces these cross-sectional patterns. The simulated cross-sectional elasticity of 0.48 is almost identical to its empirical counterpart, and the explanatory power of income is similarly close. This provides support for the model's ability to replicate the observed relationship between income and emissions. However, the main contribution of our analysis is not the level of the cross-sectional elasticity itself, but rather the distinction between transitory cross-sectional relationships and the substantially stronger relationship that emerges when households are evaluated from a lifetime perspective.

This is displayed in the final column of Table 6, which reports the corresponding estimates using PV lifetime measures of total income and emissions. In this case, the elasticity increases to approximately 0.91, implying an almost proportional relationship between PV lifetime resources and lifetime emissions. Quantitatively, the estimates imply that an additional $1,000$ Euro in annualized present-value lifetime income is associated with approximately 0.91 additional tons of lifetime GHG emissions. At the same time, the explanatory power rises markedly, with the R^2 explained by income increasing to about 0.6, which is almost twice as large as the R^2 of about 0.32 obtained from the cross-sectional specification using current income and current emissions.[20] Although the elasticity remains slightly below one, indicating persistent heterogeneity in expenditure composition and emission intensities, lifetime income emerges as a much stronger predictor of carbon footprints than current income.

Taken together, these results provide a quantitative confirmation of the underlying mechanism: while current income is a poor predictor of emissions due to life-cycle dynamics and transitory shocks, lifetime income captures the relevant resource constraint that governs consumption and, in turn, emissions.

Overall, these findings highlight a key advantage of the model: it allows us to consistently track households over the life cycle and relate lifetime economic resources to lifetime environmental impacts. While cross-sectional correlations between income and emissions are relatively weak - reflecting transitory shocks and life-cycle dynamics - the underlying lifetime relationship is much stronger. This suggests that carbon footprints are closely aligned with permanent income, even if this relationship is obscured in cross-sectional data. Therefore, the weak cross-sectional relationship does not reflect a weak structural link, but rather the fact that current income is a noisy measure of lifetime resources.

While the preceding analysis documents a substantial difference between cross-sectional and lifetime elasticities, it does not identify which model mechanisms

[20]Table E9 in Appendix E presents the regression estimates obtained when the analysis is replicated using PV lifetime labor income rather than total income. Tables E2 and E10 report analogous results when consumption is employed in place of income.

are responsible for this gap. To address this question, Table 7 decomposes the elasticity of emissions with respect to income across successive model versions and thereby isolates the contribution of individual model components, similar to the procedure in Section 5.3.2.

Table 7: The simulated emission-income elasticities across model components: cross-section vs. lifecycle

		Cross-Section	**Lifetime PV**
Model version			
1	(Basic life-cycle model)	0.914	1.020
2	(+ persistent income risk)	0.722	0.944
3	(+ transitory income shocks)	0.514	0.924
4	(+ non-homothetic preferences)	0.484	0.918
5	(+ taste heterogeneity)	0.480	0.910
6	(+ footprint heterogeneity)	0.482	0.911
Data		0.490	

Notes: Cross-sectional elasticities are evaluated at mean current income and current emissions. Lifetime elasticities are evaluated at mean present-value lifetime income and lifetime emissions. The table reports estimates from the linear specification. Corresponding quadratic and cubic specifications are reported in Appendix Table E19.

The basic life-cycle model without income risk generates a strong relationship between income and emissions. In this benchmark specification, cross-sectional elasticity is close to one and lifetime elasticity is almost perfectly proportional. Since all heterogeneity is persistent and deterministic, consumption closely tracks lifetime resources, implying a tight link between income, consumption, and emissions. Introducing persistent income risk substantially weakens the cross-sectional elasticity from 0.91 to 0.72. Households begin to smooth consumption in response to uncertainty, which reduces the contemporaneous relationship between current income and current emissions. Adding transitory iid income shocks further amplifies this mechanism and lowers the cross-sectional elasticity to 0.51, bringing the model close to the empirical estimate of 0.49. This result suggests that the weak cross-sectional relationship between income and emissions is primarily driven by consumption smoothing in the presence of income risk and life-cycle dynamics. In contrast, lifetime elasticities remain high throughout all model specifications. Even after introducing persistent and transitory income risk, the elasticity of lifetime emissions with respect to lifetime income remains close to, but still below, one. This reflects the lifetime budget constraint: while households smooth consumption intertemporally, lifetime consumption and lifetime emissions remain tightly linked to lifetime resources. The remaining model components mainly affect the elasticity at the margin. Non-homothetic preferences reduce both the cross-sectional and lifetime elasticities slightly, reflecting systematic changes in expenditure composition across the income distribution. Taste heterogeneity and footprint heterogeneity have only modest effects on the aggregate elasticity estimates. Their primary role is not to generate the gap between cross-sectional and

lifetime elasticities, but rather to account for residual heterogeneity in emissions among households with similar levels of income.

The decomposition therefore suggests that the distinction between cross-sectional and lifetime incidence arises primarily from income risk and intertemporal consumption smoothing. However, the remaining deviation from unit elasticity in the lifetime specification demonstrates that persistent differences in consumption baskets and carbon intensities continue to shape lifetime carbon footprints even after abstracting from transitory income fluctuations. We examine these remaining sources of heterogeneity in the next step using good-specific emissions.

Table 8 reports good-specific income elasticities of GHG emissions. The table compares the simulated cross-sectional relationship with the corresponding present-value lifetime relationship, focusing on the linear specification. Detailed regression results, including quadratic and cubic income terms, are reported in Appendix Tables E3-E6 for cross-sectional estimates and E11-E14 for lifetime PV estimates.

Table 8: The simulated good-specific income elasticities of emissions: cross-section vs. lifecycle

	Cross-Section	**Lifetime PV**
Food	0.346	0.658
Housing Services	0.336	0.651
Housing Energy	0.275	0.530
Transportation	0.840	1.588
Total emissions	0.482	0.911

Explanations: The table reports elasticities at the mean from linear regressions of good-specific emissions on income. The cross-sectional estimates use current simulated income and emissions. The lifetime estimates use PV lifetime total income and emissions by good. All regressions include country fixed effects. Detailed regression results, including quadratic and cubic income specifications, are reported in Appendix Tables E3-E6 and E11-E14. In Tables E15 - E18 we report the regression results using labor income.

The results reveal substantial heterogeneity across consumption categories. Food and housing-related emissions exhibit relatively low income elasticities, whereas transportation emissions are considerably more income elastic. These differences persist from a lifecycle perspective and become even more pronounced when households are evaluated using lifetime resources. In particular, transportation emissions increase more than proportionally with lifetime income. Thus, although lifetime resources explain a large share of carbon inequality, differences in consumption composition remain an important source of heterogeneity in household carbon footprints.

Overall, the preceding analysis shows that household emissions are much more closely related to lifetime resources than cross-sectional evidence suggests. Nevertheless, substantial heterogeneity remains around this relationship. While differences in consumption composition and emission intensities contribute to this

residual dispersion, it remains unclear to what extent observed emission inequality reflects persistent differences across households rather than variation within households over the life cycle. The structural model allows us to address this question directly by decomposing total emissions inequality into between-country, between-individual, and within-individual components.

To this end, we further exploit the additive decomposability of the generalized entropy index introduced in Section 3.1.2. Using the simulated lifecycle data, total emissions inequality can be decomposed as

$$GE(1) = GE^{BC} + GE^{BI} + GE^{WI}, \tag{27}$$

where GE^{BC} denotes between-country inequality, GE^{BI} captures persistent differences between households within countries, and GE^{WI} measures inequality arising within households over the lifecycle. The full derivation of this decomposition is provided in Appendix E.3 and the corresponding results are reported in Table 9.

Table 9: Decomposition of emissions inequality

		Empirical Cross-Section		Simulated Lifecycle	
Component		GE(1)	Share (%)	GE(1)	Share (%)
Between countries	(GE^{BC})	0.028	14.090	0.040	19.199
Within countries		0.168	85.810	0.170	80.801
– Between individuals	(GE^{BI})			0.115	54.468
– Within individuals	(GE^{WI})			0.056	26.333
Total		0.196	100.000	0.211	100.000

Notes: The left panel reports the standard decomposition of emissions inequality into between-country and within-country components using empirically observed household emissions. The right panel further decomposes within-country inequality in simulated cross-sectional emissions into between-individual and within-individual components. Shares are reported relative to total inequality. Countries are weighted according to their population shares.

The decomposition reveals that the majority of emissions inequality continues to arise within countries. Using population-weighted countries, between-country differences account for approximately 19.2% of total inequality, while the remaining 80.8% originates within countries. The within-country component can be further decomposed into persistent differences between households and variation within households over the lifecycle. Of total emissions inequality, 54.5% is attributable to between-individual differences, whereas 26.3% reflects within-individual lifecycle variation. Put differently, approximately one third of within-country emissions inequality arises because households experience different levels of income, consumption, and emissions over their lifecycle rather than because they differ

permanently from one another. These findings are robust to alternative weighting schemes. Appendix Table E20 reports the corresponding decomposition using equal country weights and yields qualitatively similar results.

The decomposition provides an additional perspective on the results presented above. While the elasticity analysis identifies the mechanisms governing the average relationship between lifetime income and lifetime emissions, the inequality decomposition asks how total emissions inequality is distributed across permanent differences between households and lifecycle variation within households. The stronger relationship between lifetime income and lifetime emissions does not imply that emissions inequality is solely driven by permanent differences in lifetime resources. Instead, the inequality decomposition shows that even after accounting for persistent differences across households, a substantial share of emissions inequality reflects lifecycle variation within households. This result helps explain why cross-sectional estimates substantially understate the strength of the underlying income-emissions relationship. Cross-sectional comparisons combine households with different permanent resources and households observed at different stages of their lifecycle. As a consequence, part of the observed variation in emissions reflects temporary within-household variation rather than persistent differences across households.

Taken together, the elasticity estimates and the inequality decomposition point to the same conclusion. Carbon footprints are much more closely related to lifetime resources than cross-sectional evidence suggests, yet a meaningful share of observed emissions inequality continues to arise from lifecycle dynamics and differences in consumption composition.

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 in the cross-section, both across and within countries. Our empirical analysis indicates 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.

These findings motivate a dynamic life-cycle framework that jointly models income dynamics, consumption smoothing, expenditure composition, and emission intensities. The calibrated model successfully reproduces the key cross-sectional and life-cycle patterns observed in the data.

A central contribution of this paper is to distinguish between cross-sectional and

lifetime measures of the income-emissions relationship. In the cross-section, the relationship between current income and current emissions is substantially attenuated by transitory income fluctuations and life-cycle dynamics. Using a dynamic life-cycle model, we show that once households are tracked over their entire life cycle and lifetime resources are considered, the relationship between economic resources and carbon footprints becomes substantially tighter. While the elasticity of emissions with respect to current income is only around 0.5 in the cross section, the corresponding lifetime elasticity rises to approximately 0.9 when households are evaluated using lifetime resources. This finding suggests that current income is a noisy measure of the permanent resources that ultimately govern lifetime consumption and emissions. Nevertheless, the relationship remains below one-to-one, indicating that persistent differences in consumption patterns and emission intensities continue to generate substantial heterogeneity in carbon footprints conditional on lifetime resources. Moreover, the decomposition of lifetime emissions inequality reveals that a substantial fraction of carbon inequality reflects lifecycle variation within households rather than permanent differences across households. Approximately one quarter of total emissions inequality arises within individuals over the lifecycle, highlighting the importance of distinguishing between temporary and persistent sources of carbon inequality.

An important implication of our findings relates to the evaluation of carbon pricing policies. Our findings suggest that policies based solely on current income may not accurately capture the distribution of lifetime emissions, as carbon footprints are more closely aligned with permanent income than with transitory income fluctuations. While short-run incidence remains highly relevant for households facing liquidity constraints or limited substitution possibilities in sectors such as housing energy and transportation, the broader implication of our analysis is that the distributional effects of climate policy cannot be understood from static cross-sectional measures alone. A quantitative assessment of carbon inequality requires accounting for not only for current income differences, but also for life-cycle dynamics, persistent heterogeneity in consumption behavior, and differences in carbon exposure across households. More generally, our results suggest that understanding carbon inequality requires distinguishing between temporary and permanent sources of heterogeneity. While cross-sectional measures remain informative about short-run exposure to climate policy, a life-cycle perspective reveals a much tighter connection between economic resources and carbon footprints and therefore provides an important complement for evaluating the distributional consequences of 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.

8 Bibliography

Attanasio, O. P. (1999). Consumption. *Handbook of Macroeconomics 1*, 741–812.

Attanasio, O. P. and G. Weber (1993). Intertemporal substitution, risk aversion and the euler equation for consumption. *Economic Journal 103*(416), 1–27.

Auclert, A., M. Rognlie, and L. Straub (2020). Micro jumps, macro humps: Monetary policy and business cycles in an estimated heterogeneous-agent model. *American Economic Review 110*(12), 3823–3870.

Auerbach, A. and L. Kotlikoff (1987). *Dynamic Fiscal Policy*. Cambridge University Press.

Baiocchi, G., J. Minx, and K. Hubacek (2010). The impact of social factors and consumer behavior on carbon dioxide emissions in the united kingdom: A regression based on input- output and geodemographic consumer segmentation data. *Journal of Industrial Ecology 14*(1), 50–72.

Barrell-Kane, S. and H. Yazici (2026). Carbon tax incidence over the life cycle. Working paper.

Baumol, W. J. and W. E. Oates (1988). *The Theory of Environmental Policy* (2 ed.). Cambridge: Cambridge University Press.

Bovenberg, L. (1999). Green tax reforms and the double dividend: an updated reader's guide. *International Tax and Public Finance 6*(3), 421–443.

Büchs, M., D. Ivanova, and S. Schnepf (2021, December). Fairness, effectiveness, and needs satisfaction: new options for designing climate policies. *Environmental Research Letters 16*(12), 124026.

Büchs, M. and S. V. Schnepf (2013). Who emits most? associations between socio-economic factors and uk households' home energy, transport, indirect and total co2 emissions. *Ecological Economics 90*, 114–123.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *Quarterly Journal of Economics 112*(1), 1–55.

Chakravarty, S., A. Chikkatur, H. de Coninck, S. Pacala, R. Socolow, and M. Tavoni (2009). Sharing global co2 emission reductions among one billion high emitters. *Proceedings of the National Academy of Sciences 106*(29), 11884–11888.

Chancel, L. (2022). Global carbon inequality over 1990–2019. *Nature Sustainability 5*, 931—938.

Chancel, L. and T. Piketty (2015, 11). Carbon and inequality: From kyoto to paris. Technical report.

Comin, D., D. Lashkari, and M. Mestieri (2021). Structural change with long-run income and price effects. *Econometrica 89*(1), 311–374.

Davis, S. J., K. Caldeira, and W. C. Clark (2010). Consumption-based accounting of co emissions. *Proceedings of the National Academy of Sciences of the United States of America 107*(12), 5687–5692.

Deaton, A. (1992). *Understanding Consumption*. Oxford University Press.

Druckman, A. and T. Jackson (2016). *Understanding Households as Drivers of Carbon Emissions*, pp. 181–203. Cham: Springer International Publishing.

Duarte, R., S. Miranda-Buetas, and C. Sarasa (2021). Household consumption patterns and income inequality in EU countries: Scenario analysis for a fair transition towards low-carbon economies. *Energy Economics 104*, 105614.

Eurostat (2015). *Household Budget Survey 2015 Wave EU Quality Report (Version 1)*. The European Comission.

Eurostat (2016). *Description of the data transmission for the Household Budget Survey (HBS) for the Reference Year 2015 Version: 3*. The European Comission.

Eurostat (2019). Age at which the person first received an old-age pension (2012).

Eurostat (2024). Purchasing power parities (PPPs), price level indices and real expenditures for ESA 2010 aggregates.

Fagereng, A., M. B. Holm, and G. J. Natvik (2021). Mpc heterogeneity and household balance sheets. *American Economic Journal: Macroeconomics 13*(4), 1–54.

Flechtner, S. and M. Middelanis (2025). The climate cost of inequality : trade-offs and structural effects.

Fried, S., K. Novan, and W. B. Peterman (2018). The distributional effects of a carbon tax on current and future generations. *Review of Economic Dynamics 30*, 30–46.

Fried, S., K. Novan, and W. B. Peterman (2024, None). Understanding the inequality and welfare impacts of carbon tax policies. *Journal of the Association of Environmental and Resource Economists 11*(S1), 231–260.

Geary, R. C. (1950). A note on "a constant-utility index of the cost of living". *The Review of Economic Studies 18*(1), 65–66.

Gorman, W. M. (1961). On a class of preference fields. *Metroeconomica 13*(2), 53–56.

Gough, I., S. Abdallah, V. Johnson, J. Ryan-Collins, and C. Smith (2011). The distribution of total greenhouse gas emissions by households in the uk, and some implications for social policy. *CASE Paper 152*.

Goulder, L. H. (1995). Environmental taxation and the "double dividend:" a reader's guide. *International Tax and Public Finance 2*(2).

Hardadi, G., A. Buchholz, and S. Pauliuk (2021). Implications of the distribution of german household environmental footprints across income groups for integrating environmental and social policy design. *Journal of Industrial Ecology 25*(1), 95–113.

Hassett, K. A., A. M. A. Mathur, and G. E. Metcalf (2007). The incidence of a u.s. carbon tax: A lifetime and regional analysis. *NBER Working Paper 13554*.

Heerink, N., A. Mulatu, and E. Bulte (2001). Income inequality and the environment: aggregation bias in environmental kuznets curves. *Ecological Economics 38*, 359–367.

Heindl, P. and A. Löschel (2015). Social implications of green growth policies from the perspective of energy sector reform and its impact on households. *ZEW Discussion Papers 15-012*.

Hubacek, K., G. Baiocchi, K. Feng, R. Munoz Castillo, L. Sun, and J. Xue (2017, 10). Global carbon inequality. *Energy, Ecology and Environment 2*, 1–9.

Human Mortality Database (2024). Life expectancy at age 20. University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany).

Ivanova, D., K. Stadler, K. Steen-Olsen, R. Wood, G. Vita, A. Tukker, and E. G. Hertwich (2016). Environmental impact assessment of household consumption. *Journal of Industrial Ecology 20*(3), 526–536.

Ivanova, D., G. Vita, K. Steen-Olsen, K. Stadler, P. C. Melo, R. Wood, and E. G. Hertwich (2017, may). Mapping the carbon footprint of eu regions. *Environmental Research Letters 12*(5), 054013.

Ivanova, D. and R. Wood (2020). The unequal distribution of household carbon footprints in europe and its link to sustainability. *Global Sustainability 3*, e18.

Jacksohn, A., M. A. Tovar Reaños, F. Pothen, and K. Rehdanz (2023). Trends in household demand and greenhouse gas footprints in germany: Evidence from microdata of the last 20 years. *Ecological Economics 208*, 107757.

Jorgenson, D., D. Slesnick, and P. J. Wilcoxen (1992). Carbon taxes and economic welfare. *Brookings Papers in Economic Activity: Microeconomics*, 393–431.

Jorgenson, D. W., R. J. Goettle, M. S. Ho, and P. J. Wilcoxen (2013). *Energy, the Environment and US Economic Growth*, Volume 1. Elsevier.

Kahn, M. E. (1998). A household level environmental kuznets curve. *Economics Letters 59*(2), 269–273.

Kaplan, G., B. Moll, and G. L. Violante (2018, March). Monetary policy according to hank. *American Economic Review 108*(3), 697–743.

Kaplan, G. and G. L. Violante (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica 82*(4), 1199–1239.

Leontief, W. (1936). Quantitative input and output relations in the economic systems of the united states. *The Review of Economics and Statistics 18*(3), 105–125.

Leontief, W. (1970). Environmental repercussions and the economic structure: An input-output approach. *The Review of Economics and Statistics 52*(3), 262–271.

Maier, S., S. D. Poli, and A. F. Amores (2024). Carbon taxes on consumption: Distributional implications for a just transition in the eu. JRC Working Papers on Taxation and Structural Reforms 9/2024, Seville.

McKibbin, W. J. and P. J. Wilcoxen (2013). Chapter 15 - a global approach to energy and the environment: The g-cubed model. In P. B. Dixon and D. W. Jorgenson (Eds.), *Handbook of Computable General Equilibrium Modeling SET, Vols. 1A and 1B*, Volume 1 of *Handbook of Computable General Equilibrium Modeling*, pp. 995–1068. Elsevier.

Miller, R. E. and P. D. Blair (2009). *Input-Output Analysis: Foundations and Extensions* (2 ed.). Cambridge: Cambridge University Press.

Nielsen, K. S., J. Bauer, R. Debnath, C. Emogor, S. Geiger, S. Ghai, W. Gwozdz, and U. J. J. Hahnel (2024, 09). Underestimation of personal carbon footprint inequality in four diverse countries. *Nature Climate Change 14*, 1136–1143.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences 114*(7), 1518–1523.

Pigou, A. C. (1920). *The Economics of Welfare*. Macmillan, London.

Pothen, F. and M. A. Tovar Reaños (2018). The distribution of material footprints in germany. *Ecological Economics 153*, 237–251.

Pottier, A. (2021). Expenditure-elasticity and income-elasticity of GHG emissions: a survey of literature on household carbon footprint. *FAERE Working Paper* (2021.01).

Sager, L. (2019). Income inequality and carbon consumption: Evidence from environmental engel curves. *Energy Economics 84*, 104507.

Solomon, S., D. Qin, M. R. Manning, Z. Chen, M. Marquis, K. Averyt, M. M. Tignor, and H. L. Miller (2007). *Climate change 2007: the Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Summary for Policymakers.* Cambridge: Cambridge University Press.

Stadler, K., R. Wood, T. Bulavskaya, C.-J. Södersten, M. Simas, S. Schmidt, A. Usubiaga, J. Acosta-Fernández, J. Kuenen, M. Bruckner, S. Giljum, S. Lutter, S. Merciai, J. H. Schmidt, M. C. Theurl, C. Plutzar, T. Kastner, N. Eisenmenger, K.-H. Erb, A. de Koning, and A. Tukker (2018). Exiobase 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology 22*(3), 502–515.

Stadler, K., R. Wood, T. Bulavskaya, C.-J. Södersten, M. Simas, S. Schmidt, A. Usubiaga, J. Acosta-Fernández, J. Kuenen, M. Bruckner, S. Giljum, S. Lutter, S. Merciai, J. H. Schmidt, M. C. Theurl, C. Plutzar, T. Kastner, N. Eisenmenger, K.-H. Erb, A. Koning, and A. Tukker (2021). Exiobase 3.

Stone, R. (1954). Linear expenditure systems and demand analysis: an application to the pattern of british demand. *The Economic Journal 64*(255), 511–527.

Timilsina, G. R. (2018). Where is the carbon tax after thirty years of research? *The World Bank, Policy Research Working Paper 8493*.

Violante, G. L. (2022). Heterogeneous-agent models in macroeconomics. *Journal of Economic Perspectives 36*(3), 51–74.

Weber, C. L. and H. S. Matthews (2008). Quantifying the global and distributional aspects of american household carbon footprint. *Ecological Economics 66*(2), 379–391.

Wier, M., M. Lenzen, J. Munksgaard, and S. Smed (2001). Effects of household consumption patterns on co2 requirements. *Economic Systems Research 13*, 259 – 274.

Online Appendix

Carbon Inequality in the EU

Nicole Berr
University of Regensburg

Fabian Kindermann
University of Regensburg, CEPR, HCEO, and Netspar

Julia Le Blanc
European Commission, Joint Research Centre, and CEPR

June 25, 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,[21] 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

[21] 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.).[22] 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:

$$CBA = S(I - A)^{-1}y \tag{28}$$

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[23]:

$$CBA^i = \sum_{s=1}^{m} CBA_s^i + \sum_{c=1}^{w} F_{Y_c}^i \tag{29}$$

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.

[22] 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.

[23] 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 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).[24] For example, one can assume that wood and wood products are predominantly used in the real estate construction sector. The alignment of the HBS classification system and the EXIOBASE products to the chosen matching categories is summarized in Table F1. 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 Ttransformation

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. [25]

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

[25] 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

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

$$y_{ic}^{pp} = y_{ic}^{bp} + t_{ic} + m_{ic} \quad \Rightarrow \quad y_{ic}^{bp} = \left(1 - \frac{t_{ic}}{y_{ic}^{pp}} - \frac{m_{ic}}{y_{ic}^{pp}}\right) y_{ic}^{pp}. \tag{30}$$

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".[26] 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.[27] 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

pipelines¨ are counted as part of the transport margins.

[26] 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)".

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

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[28]. The calculated indirect emission intensities are given in kg CO2 eq. per million Euro. As EXIOBASE does not differentiate between the final demand of different regions within one country we can only generate the emission intensities per country.

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

[28]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).

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.[29] 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-related 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 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:

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

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

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 observations in the bottom and top 1% of the distribution of equivalized consumption expenditure per country. Equivalized consumption expenditure was generated using the OECD equivalence scale in order to take account of differences in the households composition and to ensure comparability between households. Additionally, in the parts of our analysis that focus on income, we further restricted the sample by excluding observations with negative income.[30] The observations that are dropped as part of the data cleansing process are summerized in Table A.3.

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

Table A.1: Overview of matching categories

Code	Category	Main Category
10	**Animal-based Food**	**Food (FO)**
10.1	Meat	
10.2	Fish and seafood	
10.3	Milk and dairy products	
10.4	Other animal products	
11	**Non-animal-based Food**	
11.1	Cereal, grains, crops and bread	
11.11	Rice	
11.12	Other cereal products	
11.2	Vegetable oils and fats	
11.3	Vegetables, fruits and nuts	
11.4	Sugar	
11.5	Other food products	
12	**Beverages and Tobacco**	
12.1	Beverages	
12.2	Tobacco	
20	**Housing Services**[a]	**Housing Services (HS)**
21	**Housing Energy**	**Housing Energy (HE)**
21.1	Electricity	
21.2	Gas	
21.3	Liquid fuels	
21.4	Solid fuels	
21.5	Heat energy	
30	**Purchase and Maintenance of Vehicles**	**Transport (TR)**
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**	**Other (OT)**
22	**Housing-related Consumption**	
50	**Nondurable Consumption**	
60	**Health**	
70	**Education**	
80	**Finance**	
90	**Other Goods and Services**	

[a]: Housing Services are matched at the aggregate category level. Subcategory emissions shown in Figure 2 are allocated proportionally according to expenditure shares within the category.

Table A.2: Overview of regions

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[a]
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[b]
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

[a]: 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.
[b]: 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: Overview of observations

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.

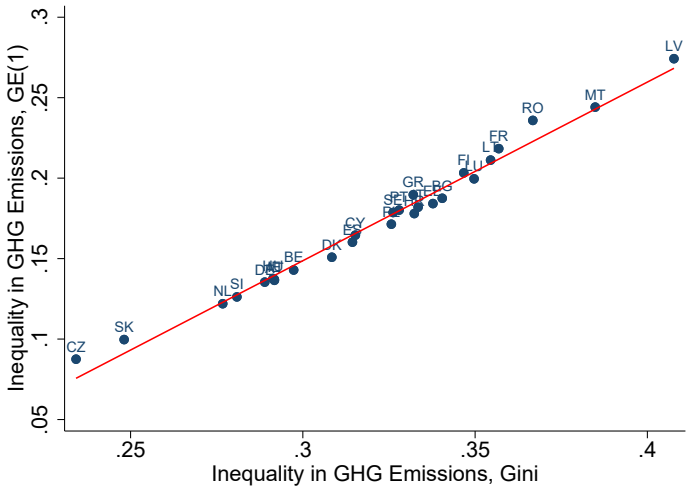
B Appendix: Empirical Analysis

Table B1: Average greenhouse gas emissions per consumption component

Component	**GHG emissions (kg)**
Animal-based Food	1,920.35
Non-animal-based Food	1,846.02
Beverages and Tobacco	273.22
Housing Services[a]	2,474.46
Electricity	1,584.52
Gas	278.37
Liquid Fuels	109.14
Solid Fuels	102.60
Heat Energy	871.67
Transp. Equim.	838.01
Fuels and Lubricants	1,269.35
Transp. Services	601.49
Restaurants/Hotels	953.35
Nondur. Cons.	2,120.11
Housing-related Cons.	1,048.12
Health	253.99
Education	94.29
Fin. Services	547.14
Other Goods and Services	504.30
Total	17,695.53

[a]: Housing Services are matched at the aggregate category level. Subcategory emissions shown in Figure 2 are allocated proportionally according to expenditure shares within the category.

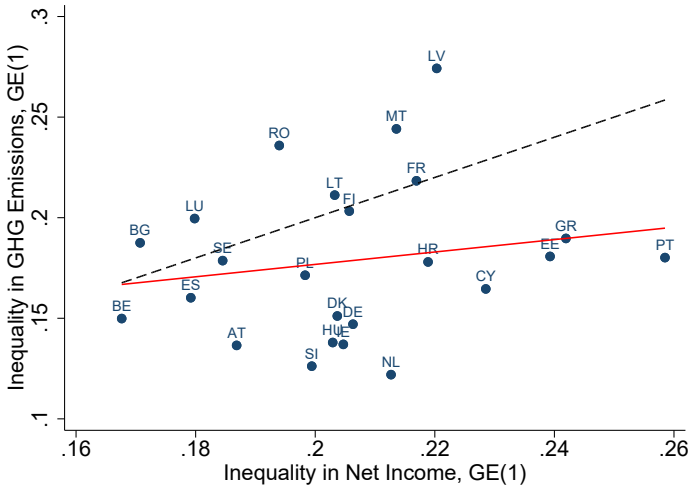
Figure B1: Gini vs. $GE(1)$ index of the household carbon footprint



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.

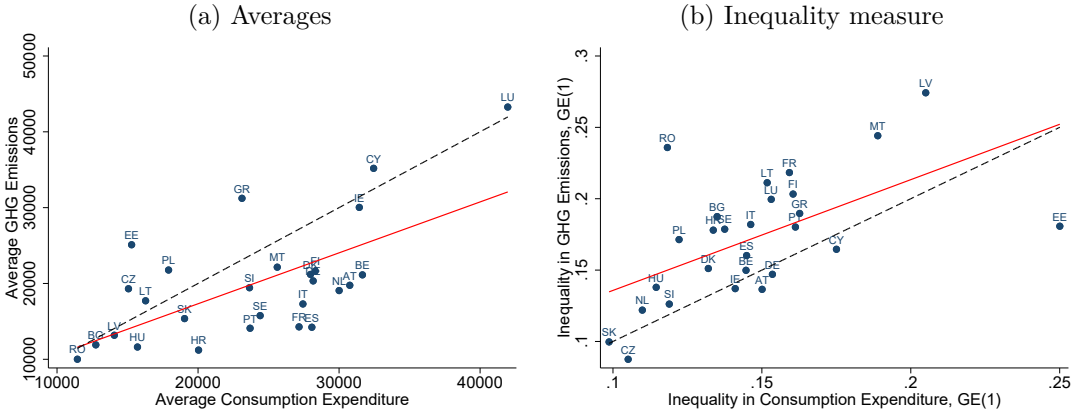
Figure B2: Correlation of emissions and household net income, excluding the Czech Republic and Slowakia



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.

Figure B3: Correlation of emissions and household consumption expenditures



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.

Table B2: The cross-sectional relation between consumption and GHG emissions

	(1)	(2)	(3)
Consumption in €	0.643***	0.634***	0.702***
	(0.00161)	(0.00753)	(0.0227)
(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.

Table B3: 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

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

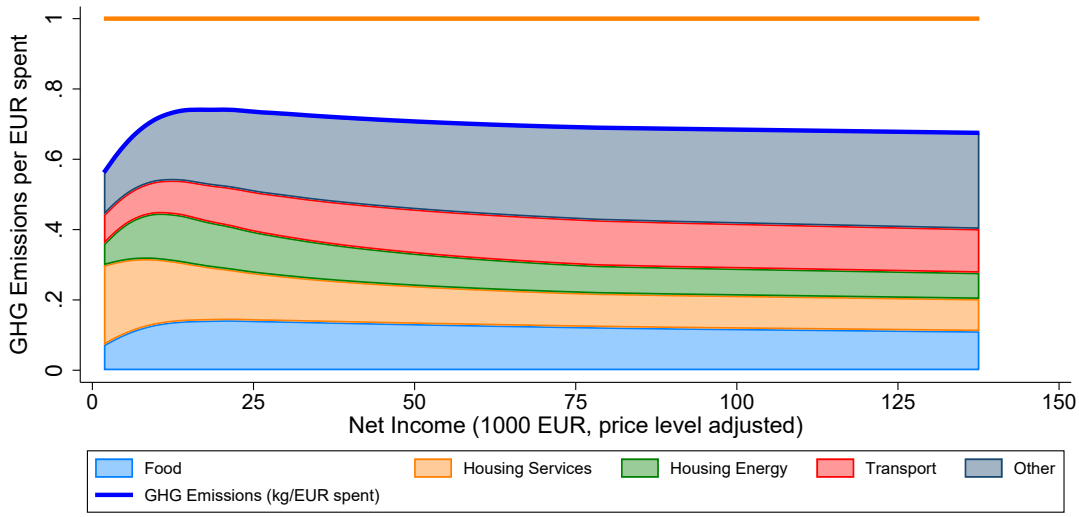
Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015. Household weights were used. Italy was excluded from the sample for consistency with prior calculations. The measure of consumption is price-level adjusted total household consumption. Robust standard errors are reported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

Table B4: 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 B4: The within-country relation between income, consumption, and emissions

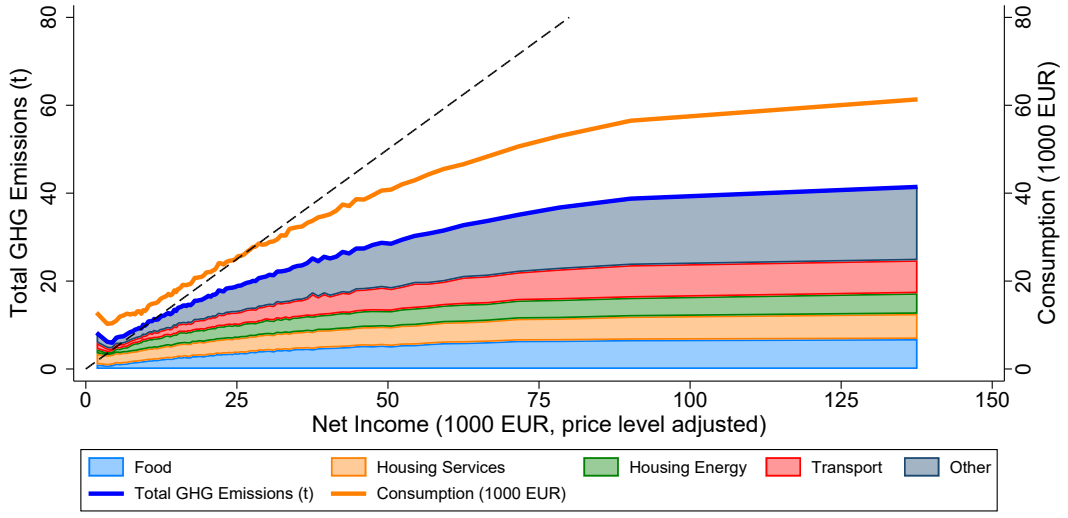


Explanations: Own calculations based on matched data from EXIOBASE 3.2 and HBS 2015.

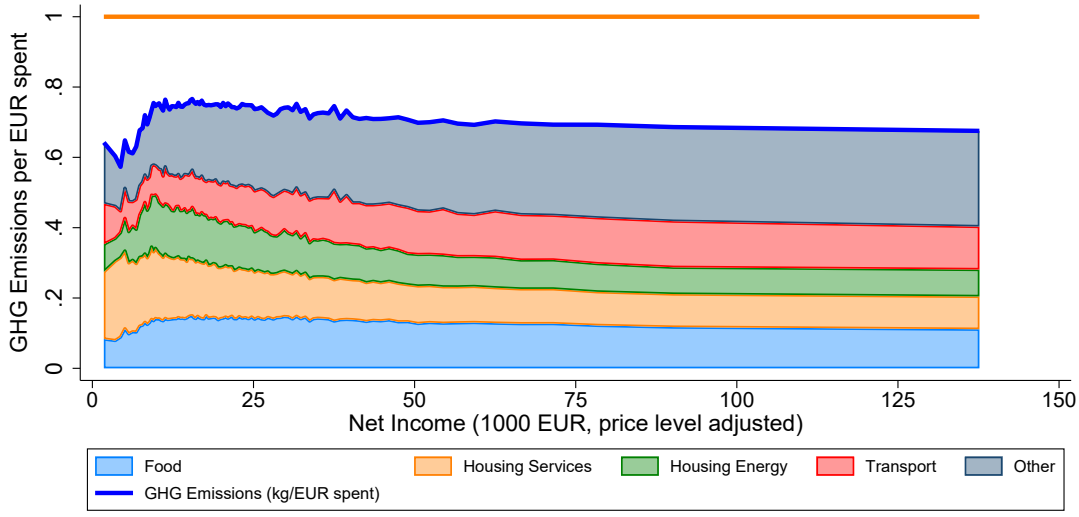
Figure B5 sheds light on the relationship between consumption levels, consumption baskets, and emissions. To achieve this, we normalized all lines in Figure 4 by the level of household expenditure. The resulting lines in Figure B5 show household GHG emissions (in kg) per Euro of household spending. There are two key points to note. First, households at the lower end of the income distribution generate slightly higher emissions per Euro spent compared to households at the upper end. The emissions intensity of consumption 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.

Figure B5: The within-country relation between income, consumption, and emissions: Relative (per Euro spent)

(a) smoothed



(b) unsmoothed



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 in Panel (a) were smoothed using local polynomial regressions.

C Appendix: Model

C.1 Solution to the Household Optimization Problem

- The household optimization problem reads

$$V(\chi) = \max_{c_j, \{c_{jg}\}_{g=1}^{G}, a^+} \; u(c_j) + \beta E\left[V(\chi^+)|\chi\right] \tag{31}$$

$$\text{s.t.} \quad \sum_{g=1}^{G} \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} = 1 \tag{32}$$

$$\text{and} \quad a^+ + \sum_{g=1}^{G} p_g c_{jg} = (1+r)a + w\kappa_j \exp(\eta+\nu) \tag{33}$$

$$\eta^+ = \rho\,\eta + \varepsilon^+, \quad \varepsilon^+ \sim N\left(0,\ \sigma_\eta^2\right), \tag{34}$$

$$\nu \sim N\left(0,\ \sigma_\nu^2\right), \quad \text{iid across households and over time.} \tag{35}$$

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

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

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

- First-order conditions read:

$$u'(c_j) = \lambda_1 \cdot \frac{\sigma-1}{\sigma} \cdot \sum_{g=1}^{G} \epsilon_g \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} \cdot \frac{1}{c_j} \tag{36}$$

$$\lambda_2 p_g = \lambda_1 \cdot \frac{\sigma-1}{\sigma} \cdot \left[\Omega_g c_j^{(1-\sigma)\epsilon_g}\right]^{\frac{1}{\sigma}} \cdot (c_{jg})^{\frac{\sigma-1}{\sigma}} \cdot \frac{1}{c_{jg}} \tag{37}$$

$$\lambda_2 = \beta E\left[V_a(\chi^+)|\chi\right] \tag{38}$$

- Summing up (37) over all goods g we get

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

- Using this again in equation (37), we obtain the expenditure share

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

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

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

- Plugging this into the expenditure function immediately yields

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

- Plugging (37) into (36), we get

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

- Together with (38), 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

$$V_a(\chi^+) = \frac{\mathcal{L}^+}{a^+} = (1+r^+)\lambda_2^+ = (1+r^+) u'(c_j^+) \cdot \frac{c^+}{\bar{\epsilon}^+ e_j^+}$$

- This leads to the Euler equation

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

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

- Intertemporal allocation:

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

- 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:

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

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

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

C.2 Market Equilibrium

To be added

C.3 Stationary Solution

To be added

...

D Appendix: Calibration

D.1 Calibration Strategy

Table D1: Calibration and estimation strategy

Estimated parameters		
Country-invariant		**Country-specific**
Parameter	Value	Parameter
Discount factor (β)	0.9500	Life-cycle income profiles (κ_j)
Intertemporal elasticity of substitution (γ)	0.5000	Variance of residual log labor earnings (Var[log(y)])
Elasticity of substitution (σ)	0.3000	Retirement age (J_r)
Persistence of income process (ρ)	0.9500	Pension replacement rate (κ_{ret})
Interest rate (r)	0.0300	Consumer prices (p_g)
Calibrated parameters		
Country-invariant		**Country-specific**
Parameter	Value	Parameter
Capital share in production (α)	0.3078	Variance of persistent labor earnings shocks (σ_η^2)
Depreciation rate (δ)	0.0720	Variance of transitory labor earnings shocks (σ_ν^2)
Wage rate (w)	1.0000	Baseline taste parameters ($\bar{\Omega}_g$)
		Non-homotheticity parameters (ϵ_g)
		Taste heterogeneity ($\sigma_{\omega,g}$)
		Baseline emission intensities ($\bar{\Phi}_g$)
		Footprint heterogeneity ($\sigma_{\phi,g}$)

Explanations: The table summarizes the calibration strategy of the model. Estimated parameters are directly obtained from household survey data and external sources, whereas calibrated parameters are chosen to match the empirical moments and stylized facts discussed in Section 3.

D.2 Model Fit

To be added

D.3 Model Decomposition of the Correlation Structure

To be added

E Appendix: Further Simulation Results

E.1 Additional Figures and Tables of the Cross-Section

Table D2: 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

Table E1: The simulated cross-sectional relation between income and GHG emissions

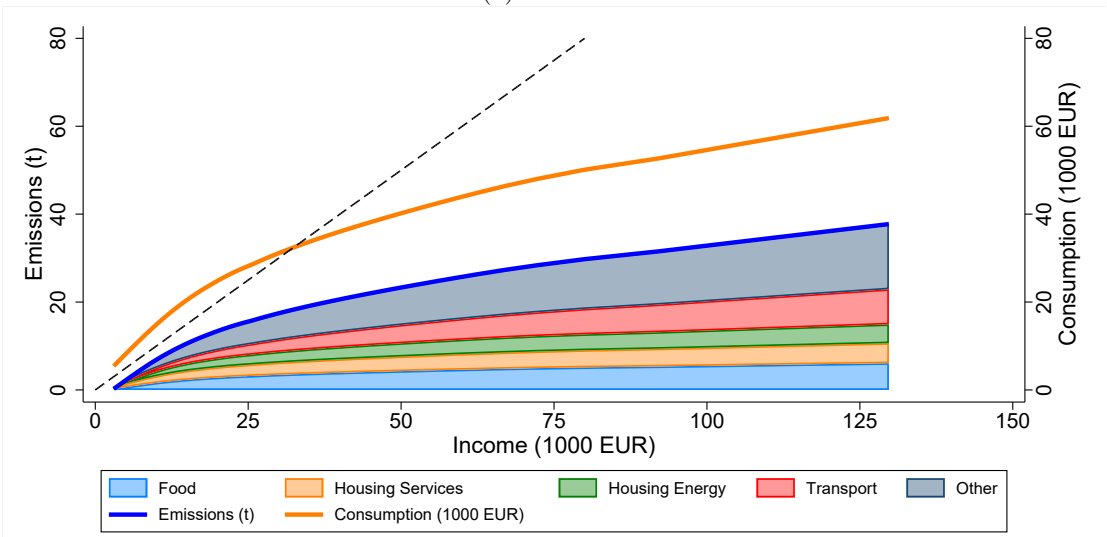
	(1)	(2)	(3)
Income in €	0.318^{***}	0.435^{***}	0.526^{***}
	(0.000266)	(0.00682)	(0.00770)
(Income in 1000€)^2		-1.048^{***}	-2.180^{***}
		(0.0651)	(0.110)
(Income in 1000€)^3			2.060^{***}
			(0.289)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.480	0.497	0.506
R^2 expl. by income	0.336	0.358	0.369
Mean income in €	26,904.200		
Mean emissions in kg	17,777.300		
Maginal effect at mean	0.318	0.378	0.413
Elasticity at mean	0.482	0.572	0.625

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

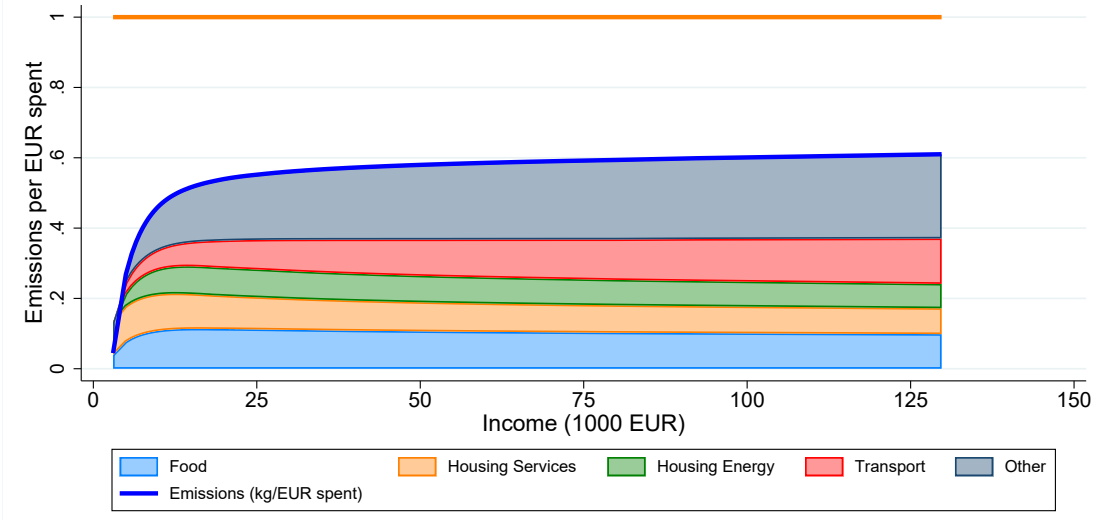
Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Figure E1: The simulated within-country relation between income, consumption, and emissions

(a) Absolute



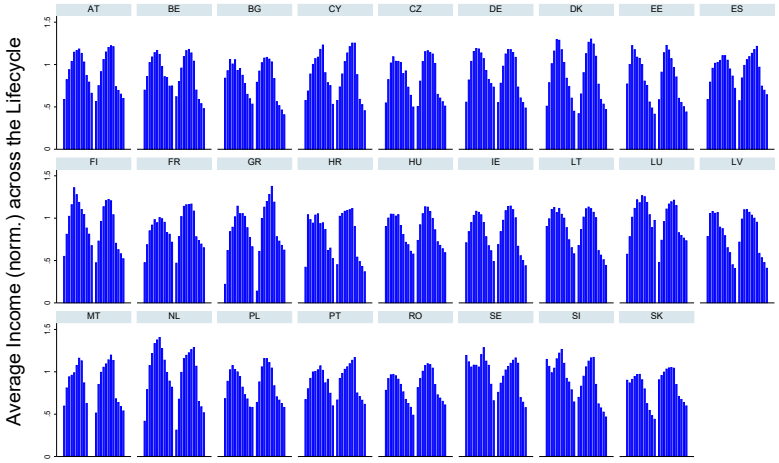
(b) Relative (per Euro spent)



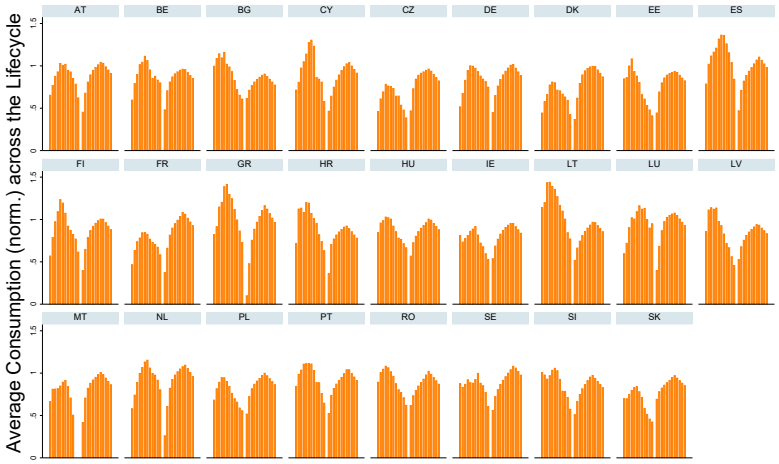
Explanations: Own calculations based on simulated life-cycle data.

Figure E2: Income, consumption and emissions across the lifecycle: empirical data vs. model

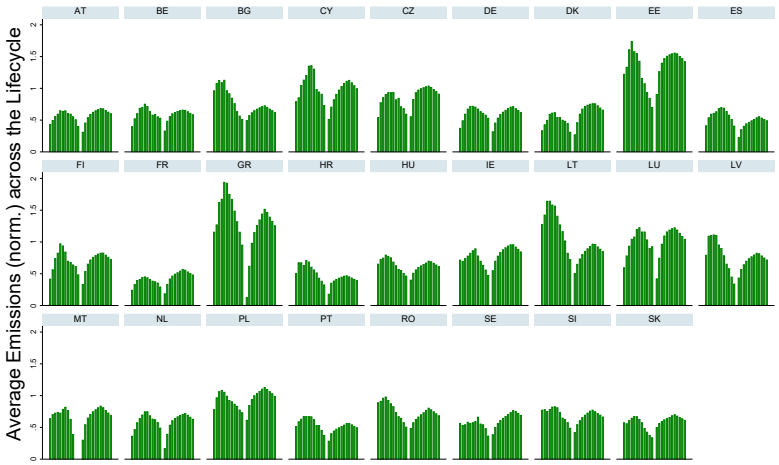
(a) Income



(b) Consumption



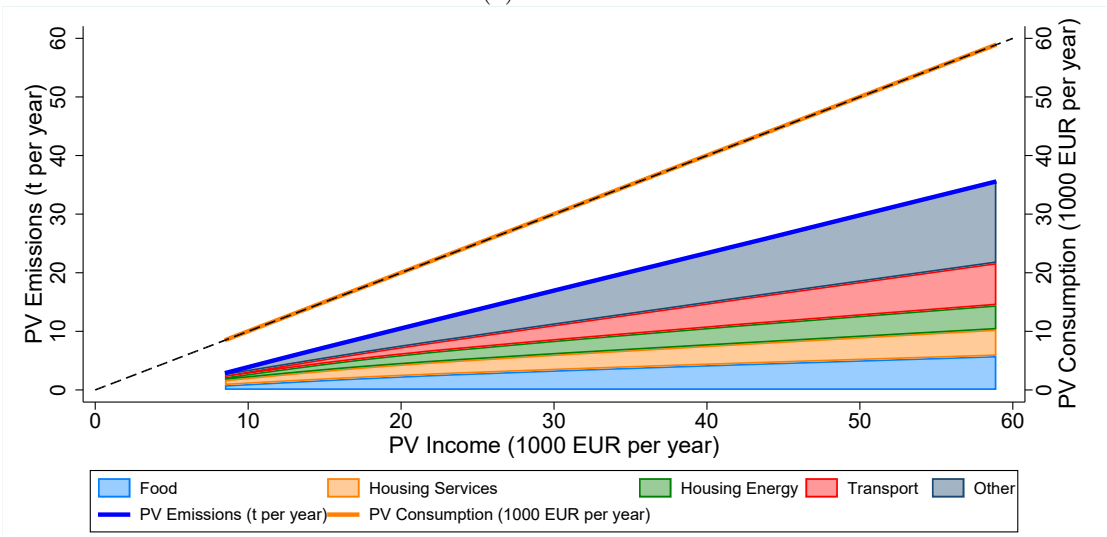
(c) Emissions



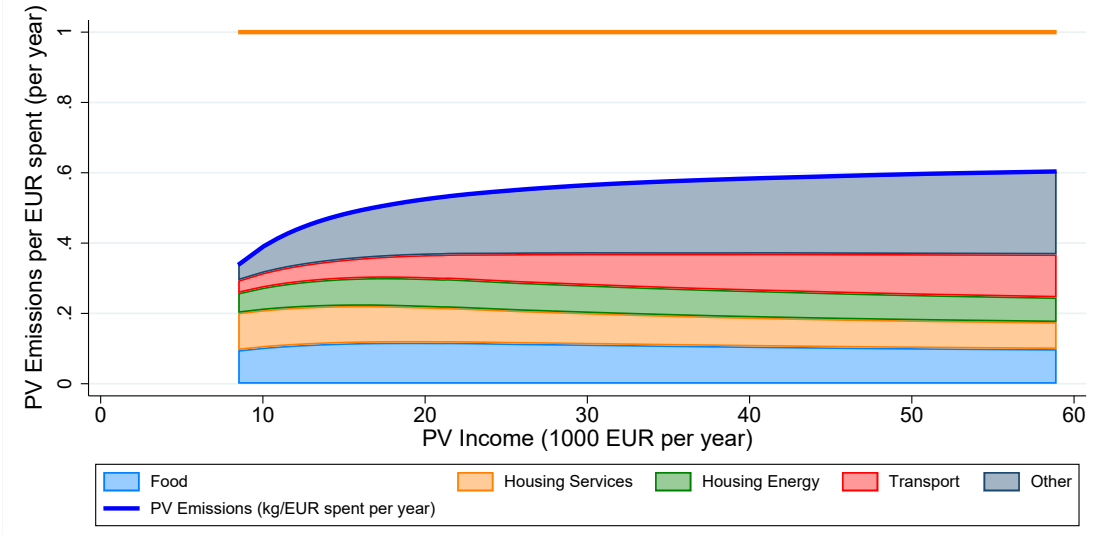
Explanations: Country-specific income, consumption and emissions are displayed across 5-year age groups. For each country, the graph on the left displays the observed data, while the graph on the right presents the corresponding model results. For comparison, the variables are normalized by the average income of working workers (with ages ≤ 59) in each country.

Figure E3: The within-country relation between annualized present value labor income, consumption, and emissions

(a) Absolute



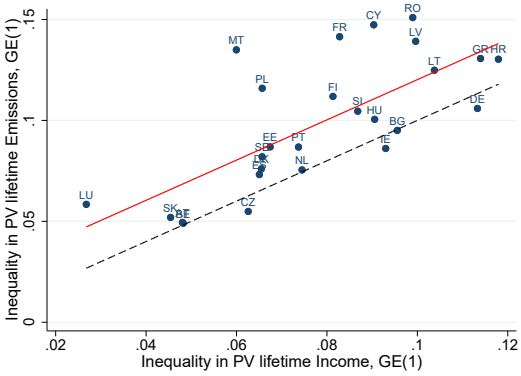
(b) Relative (per Euro spent)



Explanations: Own calculations based on simulated life-cycle data.

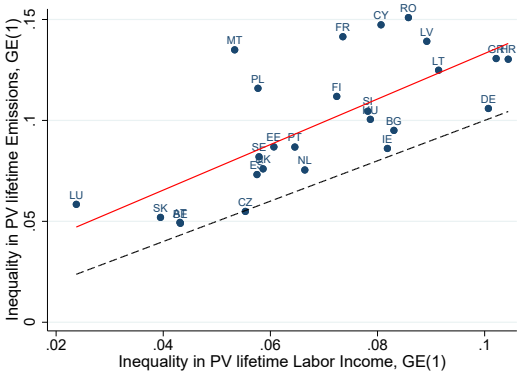
Figure E4: Correlation of inequality in present value lifetime emissions, income and expenditure

(a) Emissions and Total Income



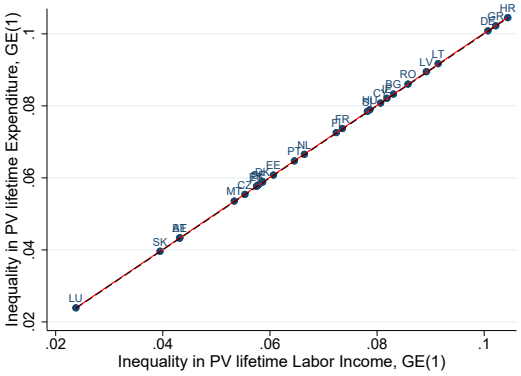
Estimated slope: 1.00, R^2: 0.51

(b) Emissions and Labor Income



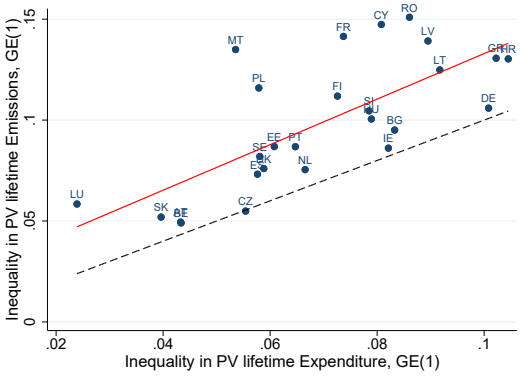
Estimated slope: 1.13, R^2: 0.51

(c) Expenditure and Labor Income



Estimated slope: 1.00, R^2: 1.00

(d) Emissions and Expenditure



Estimated slope: 1.13, R^2: 0.51

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. We derive discounted present values and compute aggregate lifetime totals from the resulting flows.

Table E2: The simulated cross-sectional relation between consumption and GHG emissions

	(1)	(2)	(3)
Consumption in €	0.654***	0.626***	0.724***
	(0.000214)	(0.000885)	(0.00182)
(Consumption in 1000€)^2		0.387***	−2.371***
		(0.0144)	(0.0576)
(Consumption in 1000€)^3			21.090***
			(0.509)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.755	0.755	0.756
R^2 expl. by consumption	0.686	0.687	0.687
Mean consumption in €	26,906.900		
Mean emissions in kg	17,777.300		
Maginal effect at mean	0.654	0.648	0.642
Elasticity at mean	0.989	0.980	0.972

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E3: The simulated cross-sectional relation between income and GHG emissions from **Food**

	(1)	(2)	(3)
Income in €	0.049***	0.070***	0.088***
	(0.0000502)	(0.00131)	(0.00157)
(Income in 1000€)^2		−0.196***	−0.417***
		(0.0125)	(0.0224)
(Income in 1000€)^3			0.403***
			(0.0587)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.336	0.350	0.358
R^2 expl. by income	0.175	0.192	0.201
Mean income in €	26,904.200		
Mean emissions in kg	3,775.200		
Maginal effect at mean	0.049	0.060	0.067
Elasticity at mean	0.346	0.426	0.474

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E4: The simulated cross-sectional relation between income and GHG emissions from **Housing Services**

	(1)	(2)	(3)
Income in €	0.033***	0.046***	0.058***
	(0.0000380)	(0.000836)	(0.00112)
(Income in 1000€)^2		−0.124***	−0.272***
		(0.00800)	(0.0160)
(Income in 1000€)^3			0.270***
			(0.0420)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.359	0.367	0.372
R^2 expl. by income	0.122	0.132	0.139
Mean income in €	26,904.200		
Mean emissions in kg	2,613.000		
Maginal effect at mean	0.033	0.040	0.044
Elasticity at mean	0.336	0.409	0.456

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E5: The simulated cross-sectional relation between income and GHG emissions from **Housing Energy**

	(1)	(2)	(3)
Income in €	0.035***	0.051***	0.064***
	(0.0000692)	(0.000941)	(0.00125)
(Income in 1000€)^2		−0.141***	−0.307***
		(0.00898)	(0.0178)
(Income in 1000€)^3			0.301***
			(0.0465)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.446	0.447	0.448
R^2 expl. by income	0.030	0.033	0.035
Mean income in €	26,904.200		
Mean emissions in kg	3,453.800		
Maginal effect at mean	0.035	0.043	0.049
Elasticity at mean	0.275	0.338	0.378

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E6: The simulated cross-sectional relation between income and GHG emissions from **Transportation**

	(1)	(2)	(3)
Income in €	0.069***	0.090***	0.102***
	(0.000118)	(0.000984)	(0.00107)
(Income in 1000€)^2		−0.182***	−0.336***
		(0.00945)	(0.0152)
(Income in 1000€)^3			0.281***
			(0.0391)
Country FE	yes	yes	yes
N	15,860,000	15,860,000	15,860,000
R^2	0.170	0.174	0.175
R^2 expl. by income	0.099	0.103	0.105
Mean income in €	26,904.200		
Mean emissions in kg	2,221.500		
Maginal effect at mean	0.069	0.080	0.085
Elasticity at mean	0.840	0.965	1.023

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

E.2 Additional Figures and Tables of Present Value Lifetime Measures

Table E7: The simulated cross-sectional vs. lifetime relation between income and GHG emissions

	Cross-Section			**Lifetime Present Value**		
	(1)	(2)	(3)	(1)	(2)	(3)
Income in €	0.318***	0.435***	0.526***	0.543***	0.588***	0.668***
	(0.000266)	(0.00682)	(0.00770)	(0.00138)	(0.00612)	(0.0167)
(Inc. in 1000€)^2		-1.048***	-2.180***		-0.023***	-0.106***
		(0.0651)	(0.110)		(0.00354)	(0.0186)
(Inc. in 1000€)^3			2.060***			0.025***
			(0.289)			(0.00616)
Country FE	yes	yes	yes	yes	yes	yes
N	15,860,000			260,000		
R^2	0.480	0.497	0.506	0.711	0.712	0.712
R^2 expl. by inc.	0.336	0.358	0.369	0.595	0.596	0.596
Mean inc. in €	26,904.2			793,737.9		
Mean em. in kg	17,777.3			472,647.6		
Elasticity at mean	0.482	0.572	0.625	0.911	0.925	0.919

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

Explanations: The left panel reports regression estimates using simulated cross-sectional household income and emissions. The right panel reports the corresponding estimates using present-value lifetime measures. Calculations are based on simulated life-cycle data and a subsample of 10,000 households per country drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E8: The simulated relation between present value lifetime total income and GHG emissions

	(1)	(2)	(3)
Income in €	0.543***	0.588***	0.668***
	(0.00138)	(0.00612)	(0.0167)
(Income in 1000€)^2		−0.023***	−0.106***
		(0.00354)	(0.0186)
(Income in 1000€)^3			0.025***
			(0.00616)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.711	0.712	0.712
R^2 expl. by income	0.595	0.596	0.596
Mean income in €	793,737.900		
Mean emissions in kg	472,647.600		
Maginal effect at mean	0.543	0.551	0.547
Elasticity at mean	0.911	0.925	0.919

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E9: The simulated relation between present value lifetime labor income and GHG emissions

	(1)	(2)	(3)
Income in €	0.646***	0.650***	0.733***
	(0.00162)	(0.00767)	(0.0225)
(Income in 1000€)^2		−0.002	−0.101***
		(0.00506)	(0.0289)
(Income in 1000€)^3			0.035**
			(0.0112)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.711	0.711	0.711
R^2 expl. by income	0.579	0.579	0.579
Mean income in €	715,100.190		
Mean emissions in kg	472,647.600		
Maginal effect at mean	0.646	0.647	0.642
Elasticity at mean	0.977	0.978	0.972

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E10: The simulated relation between present value lifetime consumption and GHG emissions

	(1)	(2)	(3)
Consumption in €	0.646***	0.650***	0.739***
	(0.00161)	(0.00765)	(0.0225)
(Consumption in 1000€)^2		−0.003	−0.107***
		(0.00504)	(0.0288)
(Consumption in 1000€)^3			0.034**
			(0.0112)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.721	0.721	0.721
R^2 expl. by consumption	0.580	0.580	0.580
Mean consumption in €	715,213.200		
Mean emissions in kg	472,647.600		
Maginal effect at mean	0.646	0.647	0.642
Elasticity at mean	0.977	0.978	0.971

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E11: The simulated relation between present value lifetime total income and GHG emissions from **Food**

	(1)	(2)	(3)
Income in €	0.085***	0.123***	0.170***
	(0.000363)	(0.00146)	(0.00395)
(Income in 1000€)^2		−0.020***	−0.068***
		(0.000820)	(0.00428)
(Income in 1000€)^3			0.014***
			(0.00138)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.434	0.437	0.437
R^2 expl. by income	0.248	0.251	0.252
Mean income in €	793,737.900		
Mean emissions in kg	101,979.000		
Maginal effect at mean	0.085	0.092	0.089
Elasticity at mean	0.658	0.712	0.695

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E12: The simulated relation between present value lifetime total income and GHG emissions from **Housing Services**

	(1)	(2)	(3)
Income in €	0.058***	0.075***	0.121***
	(0.000337)	(0.00145)	(0.00421)
(Income in 1000€)^2		−0.009***	−0.056***
		(0.000821)	(0.00459)
(Income in 1000€)^3			0.014***
			(0.00148)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.434	0.435	0.436
R^2 expl. by income	0.172	0.173	0.174
Mean income in €	793,737.900		
Mean emissions in kg	70,824.600		
Maginal effect at mean	0.058	0.061	0.059
Elasticity at mean	0.651	0.685	0.661

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E13: The simulated relation between present value lifetime total income and GHG emissions from **Housing Energy**

	(1)	(2)	(3)
Income in €	0.063***	0.093***	0.124***
	(0.000769)	(0.00301)	(0.00848)
(Income in 1000€)^2		−0.016***	−0.047***
		(0.00168)	(0.00907)
(Income in 1000€)^3			0.009**
			(0.00287)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.478	0.478	0.478
R^2 expl. by income	0.036	0.037	0.037
Mean income in €	793,737.900		
Mean emissions in kg	94,343.500		
Maginal effect at mean	0.063	0.068	0.067
Elasticity at mean	0.530	0.576	0.564

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E14: The simulated relation between present value lifetime total income and GHG emissions from **Transportation**

	(1)	(2)	(3)
Income in €	0.113***	0.086***	0.014
	(0.000976)	(0.00452)	(0.0115)
(Income in 1000€)^2		0.014***	0.088***
		(0.00266)	(0.0131)
(Income in 1000€)^3			−0.022***
			(0.00446)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.231	0.231	0.232
R^2 expl. by income	0.142	0.142	0.143
Mean income in €	793,737.900		
Mean emissions in kg	56,555.800		
Maginal effect at mean	0.113	0.108	0.111
Elasticity at mean	1.588	1.518	1.564

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E15: The simulated relation between present value lifetime labor income and GHG emissions from **Food**

	(1)	(2)	(3)
Income in €	0.100***	0.142***	0.199***
	(0.000428)	(0.00184)	(0.00525)
(Income in 1000€)^2		−0.025***	−0.093***
		(0.00119)	(0.00656)
(Income in 1000€)^3			0.024***
			(0.00248)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.431	0.433	0.433
R^2 expl. by income	0.243	0.246	0.246
Mean income in €	715,100.900		
Mean emissions in kg	101,979.000		
Maginal effect at mean	0.100	0.106	0.103
Elasticity at mean	0.699	0.745	0.724

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E16: The simulated relation between present value lifetime labor income and GHG emissions from **Housing Services**

	(1)	(2)	(3)
Income in €	0.068***	0.088***	0.152***
	(0.000397)	(0.00180)	(0.00556)
(Income in 1000€)^2		−0.012***	−0.087***
		(0.00116)	(0.00697)
(Income in 1000€)^3			0.026***
			(0.00263)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.431	0.431	0.432
R^2 expl. by income	0.168	0.169	0.170
Mean income in €	715,100.900		
Mean emissions in kg	70,824.600		
Maginal effect at mean	0.068	0.071	0.068
Elasticity at mean	0.688	0.719	0.685

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E17: The simulated relation between present value lifetime labor income and GHG emissions from **Housing Energy**

	(1)	(2)	(3)
Income in €	0.073***	0.106***	0.149***
	(0.000901)	(0.00383)	(0.0113)
(Income in 1000€)^2		−0.019***	−0.070***
		(0.00244)	(0.0140)
(Income in 1000€)^3			0.018***
			(0.00522)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.477	0.477	0.477
R^2 expl. by income	0.035	0.035	0.035
Mean income in €	715,100.900		
Mean emissions in kg	94,343.500		
Maginal effect at mean	0.073	0.078	0.076
Elasticity at mean	0.556	0.594	0.577

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E18: The simulated relation between present value lifetime labor income and GHG emissions from **Transportation**

	(1)	(2)	(3)
Income in €	0.137***	0.082***	−0.017
	(0.00115)	(0.00563)	(0.0155)
(Income in 1000€)^2		0.032***	0.149***
		(0.00378)	(0.0203)
(Income in 1000€)^3			−0.041***
			(0.00801)
Country FE	yes	yes	yes
N	260,000	260,000	260,000
R^2	0.234	0.236	0.236
R^2 expl. by income	0.146	0.148	0.148
Mean income in €	715,100.900		
Mean emissions in kg	56,555.800		
Maginal effect at mean	0.137	0.128	0.133
Elasticity at mean	1.727	1.621	1.688

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

Explanations: Own calculations based on simulated life-cycle data and a subsample of 10,000 households per country, drawn from the full simulated population of 1,000,000 households per country. Robust standard errors are reported in parentheses.

Table E19: Emission-income elasticities across model components: cross-section vs. lifecycle

	Elasticity					
	Cross-Section			**Lifecycle**		
Model version:	Linear	Quadr.	Cubic	Linear	Quadr.	Cubic
1 (Basic life-cycle model)	0.914	0.893	0.920	1.020	0.989	0.996
2 (+ persistent income risk)	0.722	0.788	0.835	0.944	0.945	0.931
3 (+ iid income shock)	0.514	0.612	0.670	0.924	0.947	0.947
4 (+ non-homotheticity)	0.484	0.574	0.627	0.918	0.926	0.920
5 (+ taste heterogeneity)	0.480	0.570	0.623	0.910	0.919	0.912
6 (+ footprint heterogeneity)	0.482	0.572	0.625	0.911	0.925	0.919
Data:	0.490	0.598	0.675			

Notes: Cross-sectional elasticities of emissions w.r.t. income are evaluated at mean income and mean emissions. Lifecycle elasticities of present value lifetime emissions w.r.t. income are evaluated at mean present value lifetime income and emissions. Columns report estimates from linear, quadratic, and cubic specifications of emissions on income.

E.3 Decomposition of the Generalized Entropy Index

We decompose the Generalized Entropy Index the following way:

$$
\begin{aligned}
GE(1) &= \frac{1}{N}\sum_{c=1}^{C}\sum_{i=1}^{N_c}\sum_{j=1}^{J}\frac{F_{icj}}{\bar{F}}\log\left(\frac{F_{icj}}{\bar{F}}\right) \\
&= \underbrace{\sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\log\left(\frac{\bar{F}_c}{\bar{F}}\right)}_{\text{between-country inequality}} + \underbrace{\sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot GE_c(1)}_{\text{within-country inequality}} \\
&= \sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\log\left(\frac{\bar{F}_c}{\bar{F}}\right) + \sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\underbrace{\left[\sum_{i=1}^{N_c}\omega_{ic}\cdot\frac{\bar{F}_{ic}}{\bar{F}_c}\cdot\log\left(\frac{\bar{F}_{ic}}{\bar{F}_c}\right)+\sum_{i=1}^{N_c}\omega_{ic}\cdot\frac{\bar{F}_{ic}}{\bar{F}_c}\cdot GE_{ic}(1)\right]}_{=GE_c(1)} \\
&= \underbrace{\sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\log\left(\frac{\bar{F}_c}{\bar{F}}\right)}_{\text{between-country inequality}} + \underbrace{\sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\left[\sum_{i=1}^{N_c}\omega_{ic}\cdot\frac{\bar{F}_{ic}}{\bar{F}_c}\cdot\log\left(\frac{\bar{F}_{ic}}{\bar{F}_c}\right)\right]}_{\text{between-individual inequality}} + \underbrace{\sum_{c=1}^{C}\omega_c\cdot\frac{\bar{F}_c}{\bar{F}}\cdot\left[\sum_{i=1}^{N_c}\omega_{ic}\cdot\frac{\bar{F}_{ic}}{\bar{F}_c}\cdot GE_{ic}(1)\right]}_{\text{within-individual inequality}} \\
&= GE^{BC} + GE^{BI} + GE^{WI}.
\end{aligned}
$$

where $N = C \cdot N_c \cdot J$ is the total number of observations, $\omega_c = \frac{popsize_c}{\sum_c popsize_c}$ population share of country c and $\omega_{ic} = \frac{J}{N_c \cdot J}$ denotes the relative weight of household i within country c. $\bar{F}$ is the average carbon footprint in the entire population, $\bar{F}_c$ is the average carbon footprint in country c, $\bar{F}_{ic}$ the lifetime-average carbon footprint of household i in country c and

$$
GE_{ic}(1) = \frac{1}{J}\sum_{j=1}^{J}\frac{F_{icj}}{\bar{F}_{ic}}\log\left(\frac{F_{icj}}{\bar{F}_{ic}}\right) \tag{39}
$$

denotes within-household lifecycle inequality $GE(1)$ for household i in country c.

In this version, each country is weighted using population weights. As a robustness check we repeat the decomposition using equal weights $w_c^p = \frac{N_c \cdot J}{N}$ instead. The results are displayed in Table E20.

Table E20: Decomposition of emissions inequality

	Empirical Cross-Section		Simulated Cross-Section	
Component	GE(1)	Share (%)	GE(1)	Share (%)
Between countries	0.028	14.090	0.048	23.407
Within countries	0.168	85.810	0.159	76.593
– Between individuals			0.108	52.223
– Within individuals			0.050	24.370
Total	0.196	100.000	0.207	100.000

Notes: The left panel reports the standard decomposition of emissions inequality into between-country and within-country components using empirically observed household emissions. The right panel further decomposes within-country inequality in simulated cross-sectional emissions into between-individual and within-individual components. Shares are reported relative to total inequality. Countries are weighted equally.

F Appendix: Product Overview (later: part of Details on data)

Table F1: 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		

Table F1 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
		01.193	Baby food		
		01.194	Ready-made meals		
		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

Table F1 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
				p90.5.d	Inert/metal/hazardous waste for treatment: landfill
				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
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]

Table F1 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
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)
22	**Housing-related 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)
				p25	Rubber and plastic products (25)[c]
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

Table F1 continued from previous page

Matching categories		HBS product allocation		EXIOBASE product allocation	
				p24.f	Additives/blending components
				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-related 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.