

Worldwide Environmental Engel Curves*

Adrien Couturier

Marion Dumas

Lucie Gadenne

Xavier Jaravel

October 2026

Preliminary

Abstract

How household greenhouse gas emissions scale with income is central to forecasting the environmental consequences of global growth. We construct a new cross-country database that harmonizes household consumption surveys for twenty-four countries with global data on direct and indirect emissions, enabling the first consistent estimation of environmental Engel curves worldwide. We show that the global elasticity of GHG emissions with respect to household expenditure is around 0.81 when evaluated using a common world-average vector of supply-chain carbon intensities per euro of expenditure. Decompositions highlight shifts across broad consumption categories and substitution toward less GHG-intensive goods within utilities as forces flattening the curve. Using retail scanner data and detailed product-level emission data, we show that quality differences and within-category heterogeneity generate only minor biases. Thus, global GHG Engel curves are largely shaped by broad consumption patterns. Overall, the contribution of demand-side non-homotheticities to long-run decarbonisation is comparable to the contribution of an entire “hard-to-abate” sector like cement, steel, or global aviation and shipping combined.

Keywords: Green transition. Non-homotheticities. Technological change.

JEL: P28

*We thank the International Growth Center (IGC) for generous financial support, Imran Rasul, Pierre Bachas and seminar participants at the Institute for Fiscal Studies for helpful suggestions and comments.

1 Introduction

How do greenhouse gas emissions vary with rising standards of living? Answering this question is essential for anticipating how global economic growth in the coming decades will translate into additional emissions. Environmental Engel curves (Levinson and O’Brien, 2015) describe the relationship between household income and the greenhouse gas (GHG) emissions embodied in the goods and services that households consume.

Despite substantial research (e.g., Wier et al., 2001; Lenzen et al., 2006; Roca and Serrano, 2007; Weber and Matthews, 2008; Büchs and Schnepf, 2013; Chancel, 2022), the slope of these curves remains debated, largely due to two data limitations. First, no existing dataset enables the consistent measurement of environmental Engel curves at a global scale — specifically, by applying a uniform, household-level estimation strategy that isolates the role of demand (as opposed to supply-chain carbon intensities) in shaping emissions across a broad set of countries at different stages of development. Second, available datasets do not incorporate micro-level quality adjustments, which may be important if higher-income households systematically purchase higher-quality varieties of goods (Bils and Klenow, 2001; Aghion et al., 2025). This paper constructs a new database to address both of these limitations.

In the first part of the paper, we combine three data sources to construct a consistent global picture of GHG Engel curves. We use (i) expenditure patterns from national household consumption surveys for 24 countries that represent 45% of world GDP and 30% of global emissions; (ii) indirect GHG emissions from Exiobase, which provides global coverage;¹ and (iii) direct emissions from household fuel combustion, sourced from the United Nations Energy Statistics Division, also with global coverage. A key step in building this database is the harmonization of consumption categories, particularly across the national surveys, which rely on heterogeneous product classifications. This process allows us to assemble a detailed dataset on household-level GHG emissions that is available for and comparable across a wide range of countries at different stages of economic development.

With this dataset in hand, we estimate the relationship between household level per-capita GHG emissions and per-capita expenditures, our proxy for income, across the world. The average slope across all households in all countries is 0.67. Unlike within-country slopes, this aggregate slope reflects both demand- and supply-side factors. Within countries, the slope arises solely from differences in expenditure shares across households, all of whom face the same GHG intensities for each consumption category. Across countries, by contrast, emissions vary due to both demand (differences in expenditure shares) and supply (differences in GHG intensities stemming from technological factors, such as the energy mix).

To isolate the role of demand, we estimate a global GHG Engel curve after imposing a common vector of carbon intensities across all countries. This vector measures emissions per euro of expenditure in each consumption category. We refer to this as ‘holding technology constant’ for brevity, but the object held fixed is more precisely the full category-level supply-chain carbon intensity per euro of expenditure, including production technologies, input-output linkages, sourcing patterns, margins, and direct fuel intensities. Using a vector averaged equally across countries, we obtain an average Engel-curve slope of

¹Indirect emissions refer to those that occur upstream of consumption, from raw material extraction to retail of the final product.

0.81. This slope remains remarkably similar when we iteratively apply each country’s technology vector to all countries. This leads to our first main result: much of the global GHG Engel curve is driven by demand factors, yielding a slope of roughly 0.81.

Using a set of decompositions, we examine the determinants of the slope of the GHG Engel curve under constant technology. Changes in spending across broad product categories account for the largest contribution to the level of the elasticity, while within-category substitution, especially within utilities, also lowers the slope. As households become richer, they allocate a greater share of spending to services - low-emissions categories - relative to utilities and, in particular, food. This flattens the GHG Engel curve. At the same time, rising expenditure on transport, a relatively high-emission category, increases the slope.

One limitation of this analysis is that emission intensities can only be measured at a relatively aggregated level (119 to 196 product categories). Moreover, within each country, our method assumes that GHG emissions per monetary unit spent within a given category are constant across households, ruling out the possibility that richer households systematically buy more expensive and higher-quality products. The second part of the paper addresses these limitations by leveraging high-quality micro data for France.

To study quality differences, we draw on retail scanner data. The dataset consists of household panels that track purchases of fast-moving consumer goods, collected by two major market-research firms (GfK and Kantar), and covers all products with barcodes. These data allow us to relax the assumption from the first part of the analysis that, within each country, GHG emissions per monetary unit spent are constant within each product category. If higher-income households systematically purchase higher-quality and more expensive varieties (as has been shown in the US by Faber and Fally, 2017), our earlier estimates of the GHG Engel-curve slope could be biased upward.

We find that unit prices indeed rise with household expenditure: on average, households in the bottom decile pay about 14 percent less per unit than those in the top decile. This however only leads to a very small bias in the GHG Engel curves estimated in the first part of the analysis. The slopes obtained from the expenditure-based and quantity-based approaches differ by less than 2 percentage points. This minimal difference reflects two facts: first, the elasticity of prices with respect to total expenditure is relatively low; second, price elasticities exhibit little heterogeneity across product categories. In principle, larger elasticities for high-carbon-intensity categories could have generated a more substantial divergence between the two approaches, but we do not find evidence of such patterns.

Finally, we draw on more granular information on GHG emissions provided by the French Environmental and Energy Agency to assess the potential role of within-category heterogeneity. This dataset covers 2,480 distinct food products—such as “lamb, cutlet, raw” or “coconut bar, chocolate-coated.” Although this level of detail is less granular than barcodes, it nonetheless offers a very high degree of granularity from an environmental perspective. Emissions estimates incorporate the typical ingredient composition, production processes, and transformations involved in generating the final product. Using this database, we obtain an estimate of the slope of the environmental Engel curve that remains very close to our baseline result. Although most carbon-intensity elasticities are positive—indicating that richer households tend to buy more carbon-intensive products—they are negative for categories with higher average carbon intensity. On average, these opposing effects offset one another across categories.

Overall, quality differences and within-category heterogeneity appear to play only a minor role in shaping the slope of the environmental Engel curve, which is our second main result. This suggests that the main drivers of the relationship are the factors identified in the first part of our analysis.

In the final part of the paper, we use the estimated environmental Engel curve in a simple calibration to quantify the importance of non-homotheticities for long-run decarbonisation. Non-homotheticities account for 4.09% of the required annual decline in global emissions intensity in our 2025–2070 calibration. Holding supply-side intensity constant, they reduce projected annual emissions by 10.83 GTCO₂e in 2070 and 4.16 GTCO₂e in 2050 relative to a homothetic counterfactual. The latter is roughly half of the emissions-reduction potential attributed by the IPCC to demand-restraint measures requiring lifestyle changes, such as reduced flying and meat consumption.

Related Literature This paper contributes to a growing literature estimating environmental Engel curves (e.g., Aghion et al., 2025; Chancel, 2022; Levinson and O’Brien, 2015; Büchs and Schnepf, 2013; Weber and Matthews, 2008; Roca and Serrano, 2007; Lenzen et al., 2006; Peters and Hertwich, 2006; Wier et al., 2001). Relative to this work, we assemble a database that spans a large set of countries at different stages of development, enabling the consistent estimation of global GHG Engel curves, holding supply-chain carbon intensities constant. In addition, we examine the potential role of quality differences using detailed retail scanner data, allowing us to assess within-category heterogeneity in emissions. Levinson and O’Brien (2019), for example, acknowledges that quality variation may bias the estimates of environmental Engel curves but are not able to verify this with their data. André et al. (2024) use similar data to ours and show as others that prices paid vary systematically with household income. We build on this by linking the retail data to life-cycle emissions data and analysing how variation in quality affects the Engel curve.

Our paper is related to recent work by Aghion et al. (2025), which also focuses on the contribution of shifts in demand in determining the global GHG Engel curve. Aghion et al. (2025) build a model in which as households become more affluent, their demand shifts to services and higher quality products, in line with empirical evidence from the US. We similarly find, using global data, that non-homothetic shifts in broad categories of consumption, notably towards services, contributes to the relative decoupling of income and emission growth. We also test their theoretical proposition that demand for higher-quality products as incomes grow will lower the emission intensity of consumption. We find that, whilst households do tend to substitute towards less emission-intensive products within broad categories, this has little to no effect on the overall emission intensity of consumption, except within utilities. This is true even when we consider very granular product-level data for the food sector.

Our findings also relate to Caron and Fally (2022), who study how consumption choices explain energy demand and GHG emissions. They calibrate a general-equilibrium model with nonhomothetic preferences using aggregate GHG emissions per large sector and trade data across countries. Our results, based on micro data and taking into account all GHGs, differ from theirs. Whereas they find an inverted-U relationship between emission intensity and income, we find a linear negative relationship across development levels, which implies a bigger role for demand non-homotheticities in reducing emissions.

Outline The remainder of the paper is structured as follows. Section 2 describes the data sources and construction steps. Section 3 presents our main results on the shape of the worldwide GHG Engel curve, holding supply-chain carbon intensities constant and abstracting from within-category heterogeneity. Section 4 examines the role of quality and within-category variation in GHG emissions. Finally, Section 5 presents a simple calibration to assess the importance of environmental Engel curve effects relative to technological progress in long-run decarbonisation.

2 Data

2.1 Data sources

Household expenditure surveys. We combine household expenditure surveys from 24 countries. For the 19 European countries in our sample, we use the Household Budget Survey (HBS) dataset provided by Eurostat, which harmonizes household expenditure surveys from European countries for the year 2010.² In addition, we use the Consumer Expenditures Survey 2011 for the United States, the National Sample Survey Organization’s Household Consumer Expenditures Survey (68th round, 2011-2012) for India, the National Survey of Household Income and Expenditure (ENIGH 2014) for Mexico, the Income and Expenditure of Households survey 2010-2011 for South Africa, and the Consumer Expenditure Survey (POF) 2008-2009 for Brazil. These surveys report expenditures at a very granular level, including for less-common expenditures (all surveys for example ask about air travel).³ We reclassify expenditure categories to follow the HBS classification for all non-European countries, convert all expenditures to 2010 euros using nominal exchange rates, and annualize all expenditures.⁴ The expenditure data measure household consumption expenditures, excluding transfers between households and taxes paid; housing is measured as a consumption flow, using actual rents for renters and imputed rents for owner-occupiers.⁵ Table A1 lists the sample size, number of items covered and recall period for each survey. In what follows we refer to the 2-digit HBS categories (food & drink, alcohol & tobacco, clothing & footwear etc) as ‘large categories’, and systematically split the category ‘housing and utility’ into two groups, the 3-digit level ‘housing’ and ‘utility’ categories as these both represent a large share of households’ budget and have very different emission intensities and expenditure elasticities. Table A2 lists the number of survey items for each of these large categories for each country in our sample (grouping together European countries, as the survey structure is the same for all of them). The level of detail provided varies across categories and countries: food, a category which represents a large share of households’ GHG emissions (see below) and for which emission intensity varies substantially across items, is systematically well documented (at least 36 categories within food in all countries) whilst some

²We exclude the UK and the Czech Republic from the original list of countries in the HBS survey as their original surveys do not contain information on imputed rents.

³Table A1 lists the number of households in the survey, the number of expenditure items recorded, and the survey recall period, for each country. Table A3 presents the share of households reporting zero expenditures on air travel in each country in the last column.

⁴The HBS classification closely resembles, but is not exactly the same as, the COICOP 2018 classification.

⁵For European HBS countries, actual rent and imputed rent are tenure-specific housing consumption flows; dwelling acquisition is capital formation and excluded from consumption expenditure. In the United States, we use the rental-equivalence measure for owner-occupied housing services, called imputed rents, rather than mortgage and maintenance costs. For the other surveys, we also use imputed rents.

categories (restaurants and accommodation, insurance and financial services) are less well documented in some countries. Our analysis below uses the survey-provided household weights to each country, normalized such that each country has equal weight, and uses total expenditures to proxy for household income, which is not measured in all surveys.

Indirect emissions data GHG emissions from consumption are the sum of direct and indirect emissions. Direct emissions refer to the emissions from the combustion of fuels by households. Indirect emissions refer to those that occur upstream of consumption, from raw material extraction to retail of the final product. Indirect emissions are obtained from the multi-region input-output database Exiobase 3 for the year 2010.⁶ This database includes an extensive set of environmental factors linked to the production of all products, including all emissions coefficients for each of the 5 main greenhouse gases for all regions and products.⁷ It contains 200 products and 49 regions (44 countries, including the 24 countries in our data, and 5 ‘rest of the world’ regions).

We obtain from Exiobase the matrix of GHG emission coefficients for each product and the Leontief inverse matrix, which provides the total output needed from each product and region to satisfy a unit of final demand of a particular product in a specific country (including all trade links). We screen the matrix of GHG emission coefficients for outliers and in some cases replace implausible values. In Appendix A.2 we provide more details on the data, explain how we transform final consumption prices to basic prices, deal with outliers and provide a series of benchmarking exercises showing that country-level consumption footprints calculated with Exiobase reproduce known rigorous estimates. Figure A6 shows that our estimated within-country elasticities of GHG emissions with respect to total expenditures are also broadly consistent with estimates found in the literature.

Exiobase covers GHG emissions from consumption of goods and services, but not emissions from asset formation. We therefore construct an alternative version of the data that replaces Exiobase’s emission coefficients for housing expenditures (rents and imputed rents) with an estimate of the GHG emitted by the construction of housing obtained from Jungclaus et al. (2024), and present results obtained with these as a robustness check.⁸

Direct emissions data Direct emissions from the combustion of fuels by households are not included in Exiobase and have to be computed separately. This is an important step because 84% of households in our data report some fuel expenditures.⁹ In the absence of fuel-specific emission intensities in monetary terms, previous studies of household-level consumption emissions have often used the aggregate direct emissions from households and distributed them equally across households, regardless of their fuel expenditures (Ivanova et al., 2017; Steckel et al., 2021). Here, we obtain instead a coefficient for total

⁶Exiobase provides estimates up to 2022, however multiple components of Exiobase are only nowcasted rather than fully updated beyond 2011, making them less reliable.

⁷These are CO₂, CH₄, N₂O, HFC and PFC.

⁸More specifically Jungclaus et al. (2024) states that the built environment was responsible for 40% of global GHG emissions in 2022, with 27% attributed to building operations (utilities) and 13% attributed to embodied carbon emissions. We therefore assume embodied GHG emissions represent 48% (0.13/0.27) of total GHG emissions in each country, and allocate these emissions to households proportionally to their housing expenditures. This increases household level emissions by roughly 8%.

⁹Table A3 shows the share of households that report non-zero expenditures for each fuel type. We see that in some countries (the US, but also many European countries) most households report using town gas or natural gas, whereas in others (Brazil, South Africa, other European countries) liquefied hydro-carbons are more commonly used.

emissions per monetary unit spent on each fuel type by taking the ratio of the total direct emissions from each fuel by households in each country (obtained from UN Energy Statistics) to the total spent on each fuel by households in that country from Exiobase, and apply this coefficient to each household based on how much they spend on each fuel.

Retail scanner data To study the role of quality differences, we leverage retail scanner data provided by Aimark, a non-profit foundation supporting the data needs of researchers in marketing and macroeconomics. The dataset consists of household panels measuring households’ purchase of fast-moving consumer goods and collected by two market research companies (GfK and Kantar). This dataset is very granular. It covers all products that have a barcode (it thus excludes fresh products that are not packaged with a barcode) and provides household expenditure, volume and price paid at the barcode-level across all retailers (except certain discounters). The data is collected by quota sampling to be representative of the entire population.

Here, we use the French dataset for the year 2019, and extract all food categories, as these are the products for which we have product-level data on emissions (see below). This dataset covers purchases over that year of 17808 households. There are 518222 unique food product barcodes categorised into 1527 distinct product types, totalling close to 21 million euros of expenditure.

Product-level emissions data The final dataset is Agribalyse. Produced by the French Environmental and Energy Agency ADEME, it provides life-cycle analyses of the environmental impacts of food products commercialised in France. The data consists of 2,480 products, such as ‘Lamb, cutlet, raw’ or ‘Coconut bar, with chocolate coating’. This is less granular than a barcode since there could be multiple barcodes corresponding to such product definitions, with variation in brand and packaging sizes. From an environmental impact point of view, however, this represents a very high level of granularity, with impacts taking into account the typical ingredient mix of the product, their mode of production, and the processing into the final product. Critically for our purposes, and unlike in Exiobase, GHG emissions of each product in Agribalyse are provided per unit of volume rather than euro.

2.2 Data construction

2.2.1 Global dataset on household emissions

Our aim with this first dataset is to build a detailed dataset on household-level GHG emissions available for, and comparable across, a large number of countries at different levels of economic development. To do so, we combine the Exiobase environmental input-output database with nationally representative expenditure surveys from 24 countries. Formally, we obtain total emissions from household h ’s expenditures e_h using the following expression:

$$e_h = \sum_j x_{hj} i_{c(h),j} \quad (1)$$

where j indexes expenditure categories, x_{hj} are total expenditures on category j by household h in Euros, obtained from the survey data, and $i_{c(h),j}$ is the emission intensity (kilos of GHG emissions per

euro) of category j in household h 's country $c(h)$, computed using the Exiobase and direct emissions data.

We define categories j at the most granular expenditure category available in both Exiobase and the COICOP/HBS classifications. In cases where the COICOP/HBS classifications are more detailed than Exiobase (e.g. Exiobase does not distinguish between different types of dairy products but many surveys do) we merge Exiobase with COICOP/HBS at a less granular level. In cases where the Exiobase classification is more detailed, we use information on aggregate demand for each category in Exiobase to compute a weighted average for the more granular level. For example, there are 14 different electricity categories in Exiobase (depending on the power source and mode of transmission) but only one electricity expenditure category in the household surveys. We assume all households in the country face the same electricity mix and compute the intensity of the average electricity mix for the country using aggregate consumption shares from Exiobase. Table A4 presents the number of emission intensity coefficients used in combining Exiobase and survey data for each country and large category. We see that the large categories 'food' and 'utilities' both have high emission intensity (see below) also have the largest number of intensity coefficients (up to 20 and a minimum of 12 for food, 10 for utilities in most countries).

To compute emission intensity for each category from Exiobase we use the matrix of greenhouse gas emission coefficients S , the Leontief input-output inverse L , and the vector of global warming potentials g , which converts each greenhouse gas emission to a GHG equivalent. We multiply the resulting matrix of GHG multipliers to a demand vector $\tilde{y}_{c(h),j}$ which represents the demand induced in basic prices by one euro of final-price spending on coicop product j in country c (see Appendix A.2). This gives us total indirect emissions intensity. For fuels, we use direct emissions intensity (emissions generated per euro spent on each fuel type, computed as explained above), $d_{c(h),j}$. We obtain:

$$i_{c(h),j} = gSL\tilde{y}_{c(h),j} + d_{c(h),j} \quad (2)$$

Figure A3 plots the distribution across countries of the indirect emission intensity coefficients for the items with the largest emission intensity in each large category. Meat of bovine animals and electricity are the coefficients with the highest indirect emission intensity (respectively 2.5kg and 4.7kg of GHG per euro on average). There is considerable variation across countries for the emission intensity of electricity, reflecting differences in the sources of fuels used to generate electricity: both South Africa and India for example rely heavily on coal.¹⁰ Appendix Figure A5 plots the distribution of the country level average budget shares and emission intensity for each large category. We see that four categories (food, utilities, transport and housing) together represent more than 60% of households' total expenditures. Three of those (food, utilities and transport) also have the highest emission intensity, with utilities having by far the highest intensity (weighted average across household of 7.6 kg per euro spent, compared to 1.8 for transport and 1.3 for food). The variation across countries is substantial for utilities, reflecting heterogeneity in both the type of fuel used for heating and cooking and the fuel mix used for electricity.

¹⁰Figure A4 similarly plots the direct emission intensity coefficients for key fuels

2.2.2 Quality-adjusted dataset on household emissions

We link household barcode-level purchases of food items in France in the Aimark dataset to Agribalyse products and HBS product categories. To do so, we apply transformer-based semantic similarity models to merge the product descriptions of barcodes in Aimark with Agribalyse products and HBS categories (Arora and Dell, 2023). This yields a harmonized dataset where each barcode can be associated with both a granular quantity-based emission intensity from Agribalyse (870 different coefficients of GHG intensity) and the coarser value-based emission intensity from our HBS-Exiobase linked data (65 different coefficients of GHG intensity). See C.1 for a detailed description of this procedure. This approach gives a mapping from each Aimark transaction indexed by a to an Agribalyse product indexed by $g(a)$ and an HBS category indexed by $j(a)$.

We use our Aimark-Agribalyse-HBS linked dataset to compare the emission elasticity of food under two different measures of carbon intensity: a quantity-based measure $i_{g(a)}^{kg}$, leveraging the match with Agribalyse, and an expenditure-based measure $i_{j(a)}^{eur}$, leveraging the match with Exiobase.

Note that these two measures are defined at different levels of granularity. To bridge the two measurements, we construct an HBS-level quantity-based intensity as a weighted average of the Agribalyse-level intensities, using household expenditure shares as weights:

$$i_{j(a)}^{kg} = \frac{\sum_{g \in j} \bar{s}_{g(a)} i_{g(a)}^{kg}}{\sum_{g \in j} \bar{s}_{g(a)}}, \quad (3)$$

where $\bar{s}_{g(a)}$ denotes the average expenditure share allocated to item $g(a)$ within category $j(a)$.

For each household h , we construct three measures of total food-related emissions summing over all expenditure items a in the Aimark dataset. The first two, with subscript c , are coarse, i.e. defined at the HBS category level $j(a)$. The first ($e_{h,c}^{eur}$), assumes constant emissions per euro spent on each category $j(a)$ whilst the other ($e_{h,c}^{kg}$) assumes constant emissions per quantity unit (typically kg) of category $j(a)$ consumed. Any systematic differences across households in these two units reflects systematic variation in the prices paid by different households within HBS categories. The third measure ($e_{h,f}^{kg}$), with subscript f , is fine-grained, i.e. defined at the Agribalyse category level $g(a)$. Here, household emissions reflect the full granularity of the Aimark-Agribalyse data. Any systematic differences between the coarse measures and this fine-grained measure reflects systematic variation between households in the emission-intensity of products they consume within a given HBS category. The three measures are defined as:

$$e_{h,c}^{eur} = \sum_a x_{ha} i_{j(a)}^{eur} \quad (4a)$$

$$e_{h,c}^{kg} = \sum_a q_{ha} i_{j(a)}^{kg} \quad (4b)$$

$$e_{h,f}^{kg} = \sum_a q_{ha} i_{g(a)}^{kg} \quad (4c)$$

where x_{ha} is household h 's expenditure on Aimark expenditure item a (in euros), q_{ha} is the quantity of expenditure item a purchased by household h (in kilograms). As described earlier, $i_{j(a)}^{eur}$ is the emission intensity of HBS category j in the French Exiobase dataset (kilograms of GHG per euro) (this

corresponds to the coefficient $i_{c(h),j}$ in equation (1) where we omit the country index for simplicity), whilst $i_{g(a)}^{kg}$ is the product-level emission intensity in the Agribalyse dataset (kilograms of GHG per unit of product).

3 Worldwide GHG Engel Curve under Constant Supply-Chain Carbon Intensities

In this section, we estimate GHG Engel curves obtained by combining household expenditure surveys and GHG emission intensity coefficients from Exiobase.

Raw GHG Engel curves. We first show the association between emissions per capita and expenditures per capita across the world.

Panel A of Figure 1 plots the raw data, reporting the logarithm of GHG emissions per capita against the logarithm of expenditures per capita for twenty-four countries. Each dot summarizes one of 50 survey-weighted expenditure bins within a country, while bold shapes highlight the 25th bin. The figure suggests that countries share broadly similar GHG Engel curve slopes.¹¹ The global Engel curve slope (elasticity of emissions with respect to total expenditures) is 0.67. This combines an elasticity of 0.71 for indirect emissions and 0.66 for direct emissions; the latter is smaller because most direct emissions come from the burning of fuel for heating and cooking, and these fuels have relatively low expenditure elasticities.

The slope of emissions as a function of expenditures in Figure 1 combines demand and supply factors. Indeed, *within* countries the slope stems only from differences in expenditure shares across households, who all face the same GHG intensities within each consumption category (see Figure A6 for within country elasticity estimates). *Between* countries, emissions can vary because of both demand (differences in expenditure shares) and supply (differences in GHG intensity due to different technologies, e.g. the energy mix).

GHG Engel Curves under constant supply-chain carbon intensities. To isolate the role of demand, we estimate a global GHG Engel curve after imposing a constant technology vector across all countries. Specifically, we define emissions under constant technology as $e_h = \sum_j x_{hj} i_j$ where i_j is an emission intensity vector common to all countries for both direct and indirect emissions. We refer to this as a “constant technology” counterfactual for brevity, but the object held fixed is more precisely the full supply-chain carbon intensity per euro of expenditure in each category: it includes production emission coefficients, input-output linkages, import sourcing, purchaser-to-basic-price conversions, transport and retail margins, and direct fuel intensities.

Panel B of Figure 1 depicts GHG emissions Engel curves using the world’s average technology vector, taking an unweighted mean of country-level coefficients within each detailed category to compute i_j , so that national survey sample sizes do not affect the technology vector. With this technology vector, the average slope of the emissions Engel curve is 0.81 (s.e. 1.86×10^{-3}), 21.67% higher than the raw GHG

¹¹The one exception is the GHG Engel curve for India, which is particularly flat. This is primarily driven by households reallocating their expenditures towards lower GHG-intensive technologies within utilities. The global elasticity is 0.74 when we exclude India.

Engel curve in Figure 1. This slope isolates demand factors alone, for this specific common supply-chain intensity vector. To assess whether the estimated slope is stable across technology vectors i_j , we repeat the analysis by applying iteratively the technology of each country to all countries. Figure 2 reports the results: the estimated world GHG emissions Engel curves are remarkably similar across all technology vectors. They range between 0.68 and 0.89, and are all above the baseline raw EEC slope.¹² This is the first key takeaway of our analysis: perhaps surprisingly, much of the world GHG Engel curve can be reproduced by demand-side differences alone, with a slope not much below unity.

Finally, note that using estimates of the embodied emissions in housing capital leaves the global elasticity essentially unchanged and slightly increases the elasticity obtained when holding technology constant. This is because, as we show below, housing has a relatively high demand elasticity, but our estimate of housing emission intensity is also higher in poorer countries.¹³

Decomposition. Which non-homotheticities account for the global Engel curve? To answer this question, we decompose the global Engel curve slope into shifts in demand between the 13 large categories (e.g. food vs utilities) and shifts within categories (e.g. between different types of fuel within utilities). Since our aim is to isolate demand factors, we conduct the analysis using the world’s average supply-chain carbon intensity vector.

Let $e_h = \sum_k e_{hk}$ denote household emissions summed over all large categories k and $c_h = \sum_k c_{hk}$ denote total household expenditure. Denoting by $s_k \equiv e_k/e$ the emission share of category k , a log-log differentiation of e with respect to c yields the following approximate decomposition of the global GHG elasticity ϵ :

$$\epsilon \approx \underbrace{\sum_k s_k \epsilon_{c,k}}_{\text{between}} + \underbrace{\sum_k s_k \epsilon_{i,k}}_{\text{within}}, \quad (5)$$

where $\epsilon_{c,k} \equiv \partial \log c_k / \partial \log c$ is the expenditure elasticity of category k , and $\epsilon_{i,k} \equiv \partial \log(e_k/c_k) / \partial \log c$ is the elasticity of the category’s GHG intensity with respect to total expenditure.¹⁴ The first sum on the right-hand side measures how much of the global elasticity can be explained by changes in expenditures between large categories (assuming no changes within categories), and the second measures how much can be explained by changes in expenditures within large categories (assuming no change across categories).

Table 1 shows the results of this decomposition. The first column reports GHG emissions shares across product categories. Three categories account for 74.02% of emissions worldwide – utilities (40.46%), food (19.16%), and transport (14.40%) – both because they represent a large share of households’ expenditures (second column) and have a high GHG intensity (third column). The table then provides for each category its GHG intensity (average kg of GHG per euro), GHG elasticity (elasticity

¹²Adding country fixed effects to the regression using the common intensity vector yields an elasticity of 0.83, within the range in Figure 2. This estimate uses within-country expenditure variation, whereas the preferred global regression also uses differences in expenditure across countries.

¹³See Appendix Figure A8 for a version of Figure 1 obtained using estimates of the embodied emissions in housing capital.

¹⁴The approximation comes from the fact that the elasticity we have estimated is a global elasticity while the log approximation is only true locally.

of emissions with respect to total expenditures) and expenditure elasticity (elasticity of expenditures on this category to total expenditures). Finally, the last two columns show the contributions of the between-category shifts and within-category shifts from Equation 5, reported as shares of the combined between and within total¹⁵.

Changes in expenditure patterns across the top four categories – utilities, food, transport and housing – together contribute 80.37% of the combined between and within total. Amongst these, utilities and food are the most GHG intensive and both have an expenditure elasticity lower than 1. Shifts away from spending on utilities and in particular food thus lower the GHG intensity of consumption as income levels rise: this can be seen by the fact that their ‘between’ contributions to the overall elasticity, whilst large, are lower than their share in total GHG emissions. Services typically have expenditure elasticities above 1, in line with known patterns of structural changes in demand as households become richer. The growth in demand for services however does not always decrease the slope of the GHG Engel curve: transport represents approximately 9.37% of expenditures and is highly GHG-intensive, so its between contribution is large – 22.54% of the combined decomposition total – and exceeds its share in total GHG emissions. Similarly, housing has a low GHG intensity but a high expenditure elasticity and expenditure share, so its contribution to the global elasticity is higher than its GHG share, though it remains relatively modest.¹⁶ Changes in expenditures in other categories play a minor role in shaping the global elasticity, because they represent a small share of consumption and have low GHG intensity.

Summing across all categories, the normalized between components add up to 1.07 and the within components to -0.07. The between term is therefore 6.52% larger than the combined total of the two terms. This shows that between-category shifts dominate the level of the approximated elasticity, while within-category reallocation lowers it. The largest negative within contribution comes from utilities, where households shift away from more polluting fuels as their expenditures rise; this contribution is 5.67% of the combined decomposition total. In the income-group results, using a vector averaged equally across countries within each group, the corresponding utilities contribution is 15.03% for the lower-expenditure group (Brazil, India, Mexico, Romania and South Africa). The higher-expenditure group comprises the remaining European countries and the United States. The larger effect in the lower-expenditure group reflects more heterogeneity in the use of different energy sources (see Tables A6 and A7). Within-category substitutions in food choices also lower the approximated elasticity.¹⁷

Table 1 also shows that most categories have a GHG elasticity below their expenditure elasticity, implying substitution toward less GHG-intensive products within those categories as household expenditures rise. Transport is the main exception, with substitution toward more GHG-intensive forms of transport; alcoholic beverages also have a small positive intensity elasticity. Most individual within-category contributions are small because the categories have low GHG shares or modest intensity elasticities.

¹⁵This total need not equal the directly estimated global elasticity, because equation 5 is only approximately valid for the estimated global regression.

¹⁶Appendix Table A8 presents results obtained when we include estimates of the GHG embedded in buildings, emitted because of their construction. When doing this, the contribution of the housing category to the global elasticity increases: it now explains nearly as much of the elasticity as utilities, because of its relatively high expenditure elasticity and GHG intensity.

¹⁷This may seem surprising since meat, which is GHG intensive, has historically been a luxury good. However, the meat effect is counterbalanced by the fact that rice accounts for a much higher share of food consumption in the lower-expenditure group and traditionally farmed rice is highly GHG intensive.

Overall, reallocation across broad categories is central to the level of the constant-technology GHG elasticity, while within-category substitution, particularly within utilities, also contributes to its being below one. These roles should be distinguished: the unnormalized between and within terms are 0.97 and -0.06, summing to 0.91, whereas the directly estimated global elasticity is 0.81. Equation 5 is therefore an approximate description of the mechanisms rather than an exact attribution of the elasticity’s distance from one.

4 GHG Engel Curves with granular consumption heterogeneity

So far we have assumed a constant emission intensity per euro spent for each HBS product category. In this section we relax two sub-components of that assumption in turn. First, we use information on prices and quantities consumed in each category and consider whether our results change when we assume constant intensity per unit consumed instead of per euro spent. Second, we allow for households to make different product choices within each category, so that the carbon intensity of each category varies across households. This the most relevant large category to focus on, as it accounts for nearly one-fourth of the GHG emissions in our sample, and is the only high-emission category for which the dataset used in the previous section may fail to capture important substitutions across products. This dataset indeed already captures most potential substitutions across utilities (mostly fuels) and transport types (the first and third highest emitting large categories). This is because Exiobase, the UN Energy Statistics, and household expenditure surveys contain very detailed information on fuels. Similarly, the transport category already distinguishes between modes of transport and is dominated by direct emissions from car fuels. To analyse quality differentiation in the food category, we utilise the Aimark-Agribalyse matched dataset described above. As this is only available for French households, we restrict our analysis to this subsample, and we use total food expenditures to proxy for total expenditures.

4.1 Constant carbon intensity per euro vs unit

We have assumed so far that the carbon intensity per monetary amount spent on a category is constant across households. This assumption is unlikely to be true if households face different prices for products in the same category. It could moreover bias our estimates of the slope of the GHG Engel curve upwards if richer households tend to buy higher-quality, more expensive products, as found in the US by Faber and Fally (2017).

We start by analyzing how the price paid for an item varies across the household expenditure distribution. For each HBS category $j(a)$ (defined in section 2.2.2 above), we plot deviation in unit prices from the average price in that category as a function of household expenditures in Figure A9. This enables us to ask whether, within a product category, richer households tend to pay higher or lower prices for the same type of goods. We find that unit prices increase with expenditure, with the bottom 10 percent of the distribution paying on average about 14 percent less per unit than the top 10 percent. The underlying within- HBS category elasticity of unit prices with respect to total expenditures is 0.054. The elasticity falls slightly, as expected, when we consider instead the variation within narrower Agribalyse categories (0.039) or within Aimark barcodes (0.031) (see Table A9).¹⁸ These patterns are

¹⁸Estimates in Table A9 are obtained by running $\log p_{ah} = \alpha_{f(a)} + \beta \log x_h + \varepsilon_{ah}$ where p_{ah} is the unit price paid

similar to those found in Faber and Fally (2017): using Nielsen scanner data for the US, which covers a wider range of retail products, they find that within product category, prices are 12% higher for the richest than for the poorest quintile.¹⁹

What do these differences in prices across households imply for the GHG Engel curve slope? Leveraging our two coarse definitions of total emissions from food items assuming either constant emissions per unit consumed or constant emissions per euro spent (defined in section 2.2.2), we compute two household-level elasticities of emissions with respect to total expenditures. Formally, we consider:

$$\log e_{h,c}^{eur} = \alpha^{eur} + \beta^{eur} \log x_h + \varepsilon_{h,c}^{eur}, \quad (6)$$

$$\log e_{h,c}^{kg} = \alpha^{kg} + \beta^{kg} \log x_h + \varepsilon_{h,c}^{kg} \quad (7)$$

where x_h is total expenditures on food by household h and $e_{h,c}^{eur}$ and $e_{h,c}^{kg}$ are as defined in equation (4a) and equation (4b) above.

We find an elasticity of emissions obtained using the expenditures approach (β^{eur}) equal to 0.997. Because this is an elasticity with respect to total food expenditures, and given an elasticity of food expenditures to total expenditures of 0.6 this is consistent with the elasticity of food GHG emissions with respect to total expenditures of 0.56 (see Table 1). The elasticity of emissions obtained using the quantity approach is as expected smaller, but very close, at 0.984. This low difference can be explained both by the relatively low elasticity of prices with respect to total expenditures, and the lack of heterogeneity in price elasticities across product categories: higher price elasticities for high-carbon intensity categories, for example, would increase the difference. Figure 3a plots the elasticity of unit prices with respect to total expenditures for each HBS category, as a function of the category's carbon intensity (grams of Co2e per kg), with circle sizes representing the category's share of total food expenditures. We see that, whilst most price elasticities are positive, they are also all reasonably small, and slightly smaller for categories with higher carbon intensity.

4.2 Within-category changes in product choices

We now leverage the granular product choice information of the Aimark-agribalyse database to consider whether the carbon intensity per unit varies within HBS food categories in a way that is correlated with total household expenditures. This could be the case if, for example, richer households bought higher quality products and higher quality products are also less carbon intensive (Aghion et al., 2025).

Formally, we regress our measure of total emissions constructed using the most granular product information on households' total expenditures:

$$\log e_{h,f}^{kg} = \alpha^{kg} + \beta^{kg} \log x_h + \varepsilon_{h,f}^{kg} \quad (8)$$

where $e_{h,f}^{kg}$ is defined using expression equation (4c) above. The only difference between $e_{h,f}^{kg}$ and the

by household h in Aimark transaction a , and $\alpha_{f(a)}$ is category fixed effects (Aimark barcodes in column 1, agribalyse categories in column 2, HBS categories in column 3).

¹⁹Our results obtained at the HBS category level are not directly comparable to those in Faber and Fally (2017) as they consider narrower Nielsen product categories. However, reproducing Figure A9 using narrower Agribalyse product categories (870 categories, versus 65 HBS categories) we get a very similar picture - see Appendix Figure A10.

emission variable $e_{h,c}^{kg}$ used in the previous sub-section is that we no longer impose a constant within HBS category carbon intensity per unit, but use the Agribalyse product-level carbon intensity measures as well as each household's expenditures on each product within each category.

We obtain an elasticity of 0.987 (see Table A10), very close to the one we obtain when imposing constant emission intensity within each category. This suggests that households with higher total expenditures do not systematically choose products with higher or lower carbon intensity per product. Figure 3b plots the elasticity of carbon intensity per unit with respect to total expenditures for each HBS category, as a function of the category's carbon intensity (grams of carbon per kg), with circle sizes representing the category's share of total food expenditures. We see that, whilst the majority of carbon intensity elasticities are positive (meaning richer households tend to buy slightly more carbon intensive products), they are negative for categories with higher average carbon intensity. On average these effects cancel out across categories.

5 Discussion and Implications

We now assess the extent to which estimates of the environmental Engel curves matter quantitatively for emissions scenarios by asking how much non-homotheticities could contribute to lowering emissions relative to estimates of the contribution of technological progress.

Setting. The key parameters for our calibration are as follows:

- Growth rate of world GDP. We assume (real) annual world GDP growth rate of 2%, denoted g ;
- Role of household consumption in total emissions. According to the literature, household consumption accounts for about 70% of total greenhouse gas emissions; this share is denoted α ;²⁰
- Climate target. Current worldwide emissions are about 40 GTCO₂e/yr but need to be brought down to about 5 GTCO₂e/yr by 2070 to limit warming to two degrees with a relatively high probability.²¹
- Environmental Engel curve. According to our estimates, emissions increase by $\varepsilon = 0.81$ when GDP increases by 1%.

Emissions in GTCO₂e in year t are given by:

$$E_t = 40 \cdot (1 + g - i)^t,$$

where g is the growth rate of (world) GDP and i the rate of decrease in the emissions intensity of GDP.

Thus, with $g = 0.02$, reaching emissions of 5 GTCO₂e in 2070 requires

$$i = 1 + g - (5/40)^{1/45} \approx 6.52\%.$$

²⁰See for instance (Halonen et al., 2024).

²¹We do not consider the 1.5 degree scenario, which appears to be out of reach under current policies.

Parameter i can be written as the sum of supply and demand factors, where the demand factors come from non-homotheticities. We have:

$$\begin{aligned} E_t &= 40 \cdot (1 + (\alpha \cdot \varepsilon + (1 - \alpha))g - i^{\text{Supply}})^t \\ &= 40 \cdot (1 + g - i^{\text{Demand}} - i^{\text{Supply}})^t, \end{aligned} \quad (9)$$

with $i^{\text{Demand}} \equiv (1 - \varepsilon) \cdot \alpha \cdot g$.

Total effort required with and without non-homotheticities. Table 2 compares the level of emissions reached in 2070 with and without the endogenous decline in emissions intensity from shifts in spending shares caused by rising living standards. We see that non-homotheticities help achieve a reduction of 10.83 GTCO₂e/yr by 2070 relative to a counterfactual homothetic scenario. Thus, absent non-homotheticities, the required effort to achieve net zero in 2070 would be about 13.26% larger.

The shares obtained from such calculations are inherently sensitive to the chosen time horizon, which motivates the structural decomposition we turn to next. Nonetheless, this exercise is informative for benchmarking the role of non-homotheticities against estimates of the contribution of demand restraint at specific horizons. The IPCC estimates that demand-side measures involving reductions in consumption—such as reduced car travel and flying, lower meat consumption, reduced material use, and the avoidance of over-consumption—could lower global emissions by around 8 GTCO₂e per year by 2050.²² At the same horizon, the non-homotheticity channel we estimate implies a reduction of approximately 4.16 GTCO₂e, i.e. roughly half as large, but arising endogenously from rising living standards rather than from deliberate, large-scale lifestyle changes.

Structural decomposition and comparisons to sectors and carbon budget. We now use the decomposition from equation (9) to compute the share of the effort achieved endogenously through non-homotheticities in consumption patterns. We have:

$$\begin{aligned} i &= i^{\text{Supply}} + i^{\text{Demand}}, \\ \frac{i^{\text{Demand}}}{i} &= \frac{(1 - \varepsilon) \cdot \alpha \cdot g}{1 + g - (5/40)^{1/45}} = \frac{0.27\%}{6.52\%} = 4.09\%, \end{aligned}$$

i.e. non-homotheticities account for about 4.09% of the required rate of decrease in the emissions intensity of GDP (0.27 out of 6.52 percentage points). In modelled IPCC pathways, many sectors account for roughly 3–7% of the total required global mitigation effort (in cumulative GHG terms). Examples include: aviation and shipping combined ($\approx$ 3–4% of global mitigation in net-zero scenarios); cement ($\approx$ 4–6%); steel ($\approx$ 5–7%); chemicals excluding plastics ($\approx$ 4–6%); agricultural CH₄ from ruminants ($\approx$ 4–5%). Thus, the contribution of demand-side non-homotheticities to long-run decarbonisation is comparable to the contribution of an entire “hard-to-abate” sector like cement, steel, or global aviation and shipping combined.

For an illustrative scale comparison, multiplying the annual intensity-reduction share of 4.09% by the carbon-budget benchmark of 1,150 GTCO₂e gives 47.05 GTCO₂e. This arithmetic comparison is

²²See Figure 5.8 in (Creutzig et al., 2022), <https://www.ipcc.ch/report/ar6/wg3/chapter/chapter-5/>.

not an estimate of an additional carbon budget or of extra years of emissions: those quantities would require integrating an explicitly specified emissions path over time.

6 Conclusion

This paper provides the first consistent cross-country estimation of GHG Engel curves using harmonized household consumption data and global emissions accounts. We show that the elasticity of household GHG emissions with respect to expenditure is around 0.81 when supply-side differences across countries are held constant. This highlights the central role of demand patterns in shaping how emissions scale with income worldwide.

We assess the extent to which within-category heterogeneity and quality differences might bias these estimates. Using detailed retail scanner data and granular product-level emission accounts, we find that such factors exert only a limited influence on the slope of the Engel curve. Differences in unit prices across the income distribution translate into only marginal adjustments, and variations in product-level carbon intensity largely cancel out across categories.

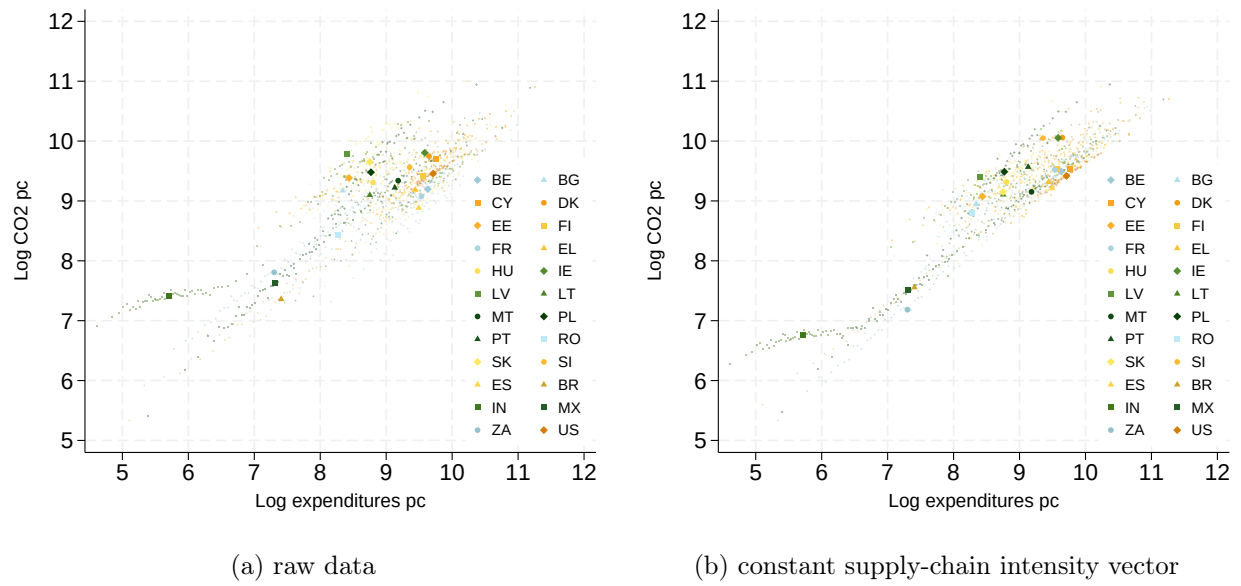
Taken together, our results indicate that global environmental Engel curves are primarily driven by broad shifts in consumption bundles as income rises. This has important implications for projecting future emissions paths. Our estimates indicate that non-homotheticities contribute to long-run decarbonisation on a scale comparable to that of an entire hard-to-abate sector, such as cement, steel, or global aviation and shipping combined, and amount to roughly half of the emissions-reduction potential attributed to demand-restraint measures requiring lifestyle changes, such as reduced flying and meat consumption.

References

- Aghion, Philippe, Timo Boppart, Michael Peters, Matthew Schwartzman, and Fabrizio Zilibotti**, “A theory of endogenous degrowth and environmental sustainability,” CEP Discussion Papers dp2086, Centre for Economic Performance, LSE Mar 2025. 1, 4.2
- André, Mathias, Alexandre Bourgeois, Emmanuel Combet, Matthieu Lequien, and Antonin Pottier**, “Challenges in measuring the distribution of carbon footprints: The role of product and price heterogeneity,” 2024, *220*, 108122. 1
- Arora, Abhishek and Melissa Dell**, “LinkTransformer: A unified package for record linkage with transformer language models,” 2023. 2.2.2
- Bils, Mark and Peter J. Klenow**, “Quantifying Quality Growth,” *American Economic Review*, 2001, *91* (4), 1006–1030. 1
- Bruckner, Benedikt, Klaus Hubacek, Yuli Shan, Honglin Zhong, and Kuishuang Feng**, “Impacts of poverty alleviation on national and global carbon emissions,” 2022, *5*, 311–320. B.3.1
- Büchs, Milena and Sylke V. Schnepf**, “Who emits most? Associations between socio-economic factors and UK households’ home energy, transport, indirect and total CO2 emissions,” *Ecological Economics*, 2013, *90*, 114–123. 1
- Caron, Justin and Thibault Fally**, “Per capita income, consumption patterns, and CO2 emissions,” *Journal of the Association of Environmental and Resource Economists*, 2022, *9* (2), 235–271. 1
- Chancel, Lucas**, “Global carbon inequality over 1990–2019,” *Nature Sustainability*, September 2022, pp. 1–8. 1, B.3.1, A6
- Creutzig, Felix, Joyashree Roy, Patrick Devine-Wright, Julio Díaz-José, Frank W. Geels, Arnulf Grubler, Nadia Maïzi, Eric Masanet, Yacob Mulugetta, Chioma D. Onyige, Patricia E. Perkins, Alessandro Sanches-Pereira, and Elke U. Weber**, “Demand, services and social aspects of mitigation,” in “Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change,” Cambridge University Press, 2022, pp. 503–612. 22
- Faber, Benjamin and Thibault Fally**, “Firm Heterogeneity in Consumption Baskets: Evidence from Home and Store Scanner Data,” January 2017. 1, 4.1, 19
- Halonen, Vilma, Anna Claudelin, Ville Uusitalo, and Suvi Konsti-Laakso**, “The potential of individuals to reduce greenhouse gas emissions through their own actions: a case of a suburb in Finland,” *Discover Sustainability*, 2024, *5* (191). 20
- Ivanova, Diana, Gibran Vita, Kjartan Steen-Olsen, Konstantin Stadler, Patricia C Melo, Richard Wood, and Edgar G Hertwich**, “Mapping the carbon footprint of EU regions,” *Environmental research letters: ERL [Web site]*, May 2017, *12* (5), 054013. 2.1

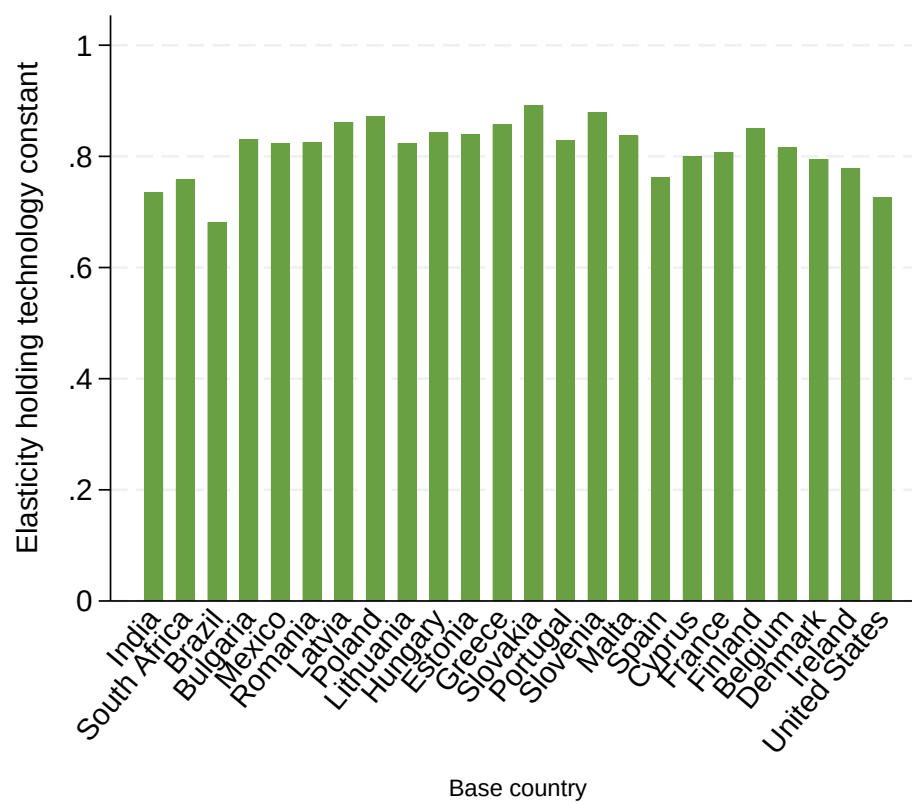
- Jungclauss, Matt A., Nicholas Grant, Martín I. Torres, Jay H. Arehart, and Wil V. Srubar**, “Embodied carbon benchmarks of single-family residential buildings in the United States,” *Sustainable Cities and Society*, 2024, *117*, 105975. 2.1, 8
- Lenglart, Fabrice, Christophe Lesieur, and Jean-Louis Pasquier**, “Les émissions de CO₂ du circuit économique en France,” *L’économie française – Comptes et dossiers*, Insee Références, INSEE 2010. A.2.4
- Lenzen, Manfred, Mette Wier, Claude Cohen, Hitoshi Hayami, Shonali Pachauri, and Roberto Schaeffer**, “A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan,” *Energy*, February 2006, *31* (2), 181–207. 1
- Levinson, Arik and James O’Brien**, “Environmental Engel Curves,” January 2015. 1
- and —, “Environmental Engel curves: Indirect emissions of common air pollutants,” *The Review of Economics and Statistics*, March 2019, *101* (1), 121–133. 1
- Peters, G P and E G Hertwich**, “The importance of imports for household environmental impacts,” *Journal of Industrial Ecology*, 2006. 1
- Pottier, Antonin**, “Expenditure elasticity and income elasticity of GHG emissions: A survey of literature on household carbon footprint,” 2022, *192*, 107251. B.3.1
- Roca, Jordi and Mònica Serrano**, “Income growth and atmospheric pollution in Spain: An input–output approach,” *Ecological Economics*, 2007, *63* (1), 230–242. 1
- Stadler, Konstantin, Richard Wood, Tatyana Bulavskaya, Carl-johan Södersten, Moana Simas, Sarah Schmidt, and Arkaitz Usubiaga et al.**, “EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables,” *Journal of Industrial Ecology*, 2018, *22* (3), 502–515. A.2.1
- Steckel, Jan, Ira Dorband, Lorenzo Montrone, Hauke Ward, Leonard Missbach, Fabian Hafner, Michael Jakob, and Sebastian Renner**, “Distributional impacts of carbon pricing in developing Asia,” *Nature Sustainability*, September 2021, pp. 1–10. 2.1
- Weber, Christopher L. and H. Scott Matthews**, “Quantifying the global and distributional aspects of American household carbon footprint,” *Ecological Economics*, 2008, *66* (2), 379–391. 1
- Wiedmann, Thomas, Richard Wood, Jan C Minx, Manfred Lenzen, Dabo Guan, and Rocky Harris**, “A carbon footprint time series of the UK – results from a multi-region input–output model,” *Economic Systems Research*, March 2010, *22* (1), 19–42. A.2.4
- Wier, Mette, Manfred Lenzen, Jesper Munksgård, and Sinne Smed**, “Effects of household consumption patterns on CO₂ requirements,” *Economic Systems Research*, 2001, *13* (3), 259–274. 1

Figure 1 : GHG Engel Curves



Notes: This figure plots log GHG emissions per capita against log expenditures per capital for all countries in our sample. Panel (a) plots emissions obtained by combining household expenditure surveys and country-specific emission coefficients, Panel (b) uses the same average emission coefficient for all countries, see the text for more details.

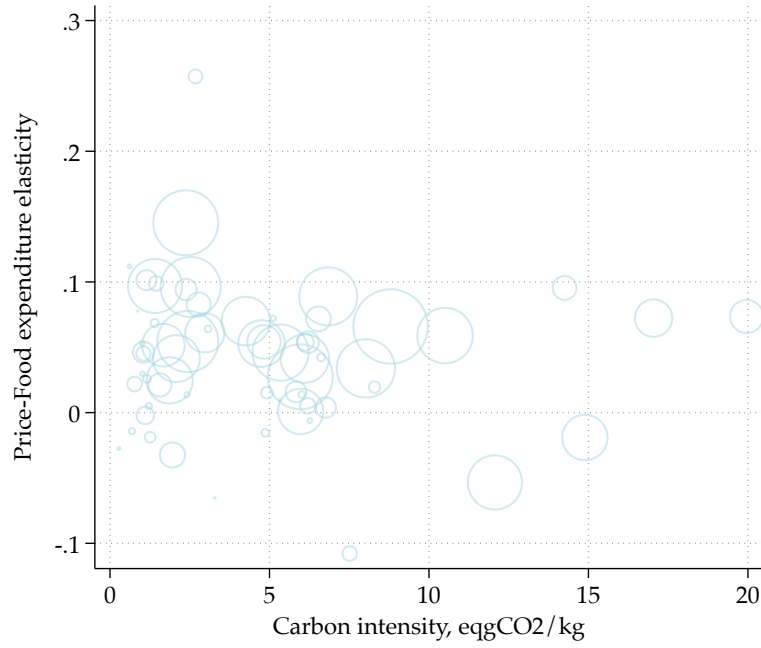
Figure 2 : GHG Engel Curve Slopes, Under Common Supply-Chain Carbon Intensities



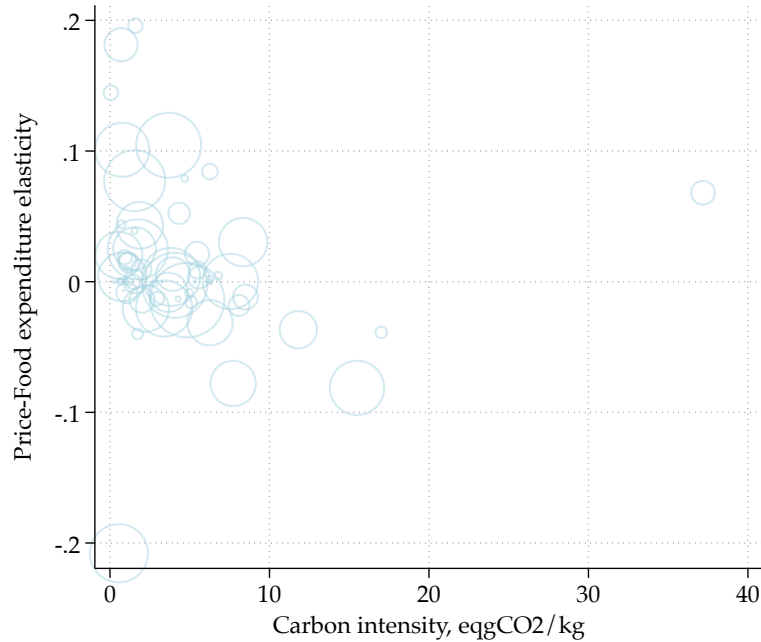
Notes: This figure reports the estimated slope of the world's emissions Engel curve depending on the base country used to set the supply-chain carbon intensity vector applied to all countries.

Figure 3 : Elasticities with respect to total expenditures as a function of category-level carbon intensity

(a) Elasticity of unit prices with respect to total expenditures



(b) Elasticity of carbon intensity with respect to total expenditures



Notes: Panel (a) plots the elasticity of unit prices with respect to total food expenditures, obtained at the HBS category level, as a function of the category's carbon intensity (grams per kg). Panel (b) plots the elasticity of carbon intensity per unit with respect to total food expenditures, as a function of the category's average carbon intensity (grams per kg). Prices are obtained using the sample of French households in the Aimark data. Carbon intensities per kg are obtained from the Agribalyse dataset.

Table 1 : Decomposition of GHG Engel Curves

Product category	GHG Share	Exp. Share	GHG Intensity	GHG Elasticity	Exp. Elasticity	Between	Within
Utilities	0.40	0.10	6.27	0.70	0.83	0.37	-0.06
Food	0.19	0.23	0.94	0.57	0.61	0.13	-0.01
Transport	0.14	0.09	1.66	1.51	1.42	0.23	0.01
Housing	0.06	0.20	0.28	1.24	1.24	0.08	0.00
Furnishings	0.03	0.05	0.85	0.95	1.04	0.04	0.00
Miscellaneous	0.03	0.07	0.47	1.24	1.31	0.05	0.00
Clothing	0.03	0.04	0.68	0.96	0.99	0.03	0.00
Health	0.03	0.04	0.85	0.80	0.97	0.03	-0.01
Recreation & culture	0.03	0.06	0.48	1.43	1.43	0.05	0.00
Restaurants & hotels	0.02	0.04	0.32	2.05	2.05	0.04	0.00
Alcoholic beverages	0.01	0.03	0.56	0.80	0.79	0.01	0.00
Communication	0.01	0.04	0.27	0.80	0.94	0.01	0.00
Education	0.00	0.01	0.21	1.13	1.13	0.00	0.00

This table decomposes the global GHG Engel curve obtained using the supply-chain carbon-intensity vector averaged equally across countries. GHG and expenditure shares, intensities, and elasticities are shown by broad category. The final two columns report each category's between- and within-category contribution as a share of their combined total. All category elasticities are estimated against total expenditure on a common sample within each category. Contributions are normalized before rounding. Categories are ordered by GHG share.

Table 2 : Impact of Non-homotheticities on Worldwide Greenhouse Gas Emissions

2025 emissions:	40.00 GTCO ₂ e/yr
2070 emissions with $i = 0$ and $g = 2\%$:	97.51 GTCO ₂ e/yr
2070 emissions with $\varepsilon = 0.81$, $i^{\text{Supply}} = 0$, and $g = 2\%$:	86.68 GTCO ₂ e/yr
2070 emissions target:	5.00 GTCO ₂ e/yr

Notes: This table presents total global GHG emissions under different scenarios. See the text for computation details.

A Datasets

A.1 Consumer expenditure surveys

We use household expenditure surveys from 24 countries. For the 19 European countries we use the Household Budget (HBS) dataset provided by Eurostat, which harmonized household expenditure surveys from European countries for the year 2010. We exclude the UK and the Czech Republic from the original list of countries in the HBS survey as their surveys do not contain information on imputed rents. In addition, we use the Consumer Expenditures Survey 2011 for the United States, the National Sample Survey Organization’s Household Consumer Expenditures Survey (68th round, 2011-2012) for India, the National Survey of Household Income and Expenditure (ENIGH 2014) for Mexico and the Income and Expenditure of Households survey 2010-2011 for South Africa. Each survey contains household weights designed to make the survey nationally representative, we use these in all computations in the paper. Appendix Table A1 lists the countries in our sample, the number of households in each survey, the number of expenditure items documented in the survey and the recall period used. Table A2 reports the number of survey items per large category in each country, grouping together all European countries as the number of items are the same in all these countries. Table A3 presents the (unweighted) share of households that report no expenditures for survey items in each country of specific interest: fuels (for which we compute direct emission intensity factors, see the text for more details) and air transport (which have high emission intensity and for which recall may be a concern).

A.2 Exiobase 3

A.2.1 Background information on Exiobase 3

Exiobase 3 is a multi-region input-output (MRIO) database running from 1995-2022, with an extensive set of environmental factors linked to each product, including greenhouse gas emission coefficients for all regions and products. It includes $P = 200$ products and $R = 49$ regions (44 countries, and 5 rest of the world regions), making it one of the most comprehensive MRIOs with environmental stressors. The design choices of Exiobase around the product typology reflect a balance between ensuring adequate data availability across countries and capturing the distinctions between sectors that create high, but diverging, environmental pressures, such as agriculture, mining, and energy extraction and, for e.g., between meat-based and plant-based food products, or between different power industries.

The construction of the Exiobase 3 time series is documented in Stadler et al. (2018). It consists of multiple constituent datasets. The first building block are the monetary supply-use tables (MSUTs). These are compiled by harmonising and balancing raw datasets from the UN System of National Accounts, national statistics, material flow databases (e.g. FAOSTAT), UN trade service database and the BACI database. The second building block are the energy supply-use tables (ESUTs). The ESUTs use the IEA’s extended energy balances, detailing the domestic supply and use of around 60 primary and secondary energy products. These balances are processed to conform to the resident principle instead of the territory principle. This means that energy flows capture the activities carried out by the resident units of a country, independent of where these activities take place. This mainly affects international transport activities. Transport models have been built to properly allocate the use of fuels from interna-

tional fishing activities, as well as from international marine and aviation bunkers. The energy flows are then allocated to the 200 products by means of a variety of auxiliary data sets. The third building block are the emission accounts. In this project, we focus on air emissions of GHG. To capture the emissions arising from combustion processes, the ESUTs described above are combined with the emission factors retrieved from the TEAM model. The TEAM model has been filled with emission factors from various sources, including from the Guidelines for National Greenhouse Gas and Air Pollutant Inventories, and from the GAINS model (Amann 2009), and is updated annually. Emissions arising from non-combustion processes are computed using data collected from various sources (e.g., UN Statistics, U.S. Geological Survey, British Geological Survey, FAOSTAT, etc.).

A.2.2 Limitations

Exiobase 3 does not include the land-use impacts of production. It allows the computation of the environmental impacts of capital asset formation, but does not assign these capital assets to flows of products. Hence, the environmental impacts of the capital costs of production are not factored in.

A.2.3 Handling outliers in Exiobase

The only adjustment we make to the Exiobase dataset is to screen outlier values in the matrix of emission coefficients and impute a replacement value. We found that these outliers occur when a country’s output is small relative to other countries’ output. In these cases, the coefficient can easily be mis-estimated because it becomes harder to accurately attribute energy flows and other environmental inputs to that sector, and errors are magnified by the small output used in the denominator. These outlier values are particularly problematic for energy consumption, where for example, renewable energy sectors, which were still very small in most countries in 2010, may erroneously be given very high emission coefficients. In the case of energy products, we define an outlier as any coefficient which is more than 10 times the median coefficient across representative Exiobase regions, and we replace these outliers by the median coefficient (in rare cases where the median is 0, we replace by the mean instead). One exception is the category *Steam and hot water supply services*. In this case, we replaced coefficients by the median when coefficients are more than 2 times the median. This is because we found that this category constituted an implausibly large proportion of household emissions in a number of European countries which fell below our chosen threshold of 10 times the median. This rescaling operation was also applied to a few other non-energy commodities with high GHG emissions, such as *Meat animals nec*, *Sand and clay*, *Paddy rice*.

A.2.4 Benchmarking Exiobase with other country-level GHG footprint estimates

There is no gold standard dataset that tracks greenhouse gas emissions from their source to final consumption through global supply chains. Instead, we have access to several multi-regional input-output databases that include estimates of emission intensities in each sector and country, each of which has different strengths and weaknesses in terms of granularity, coverage and quality of harmonisation, and unknown amount of measurement error. We chose Exiobase because it is the most granular, includes all greenhouse gases and all countries in our sample. To assess the extent to which our results may

hinge on idiosyncratic measurement errors in Exiobase, we thus benchmark country-level consumption-based emissions obtained directly from Exiobase against several other sources. Here we use aggregate household demand in the Exiobase database, leaving aside the household-level expenditure data .

Figure A1 compares data from the Global Carbon Project (used in Our World in Data) to Exiobase results for the European countries in our data. The Global Carbon Project uses Global Trade Analysis Project (GTAP), another environmentally extended MRIO, with different approaches to harmonizing data and different aggregation and disaggregation strategies. Figure A1 shows that the agreement is good between GTAP and Exiobase at the aggregate country level.

We then compare Exiobase results to results from the statistical offices of the UK and France, which use their own environmental accounts and I-O tables (see Wiedmann et al., 2010; Lengart et al., 2010). In the case of the UK, we check that we reproduce the time trends documented by Defra, which are based on Wiedmann et al. 2010). Figure A2 shows the time trends are very similar to that reported by Defra.

Pasquier 2010 provides INSEE estimates of France’s consumption-based greenhouse gas household emissions for 2005. Total emissions from household consumption were estimated to be 376 Mt CO₂. Exiobase results for France in 2005 gives us 398 MtCO₂ for household consumption (5% higher than INSEE). INSEE’s estimate of the total emissions for all forms of consumption stands at 550 MtCO₂, while Exiobase gives us 617 MtCO₂ (10% higher than INSEE).

A.3 Scanner Data

A.3.1 Aimark Data

The scanner data are provided by AiMark, a non-profit foundation that promotes research in marketing and macroeconomics. The data cover household purchases of so-called fast-moving consumer goods (also known as consumer-packaged goods), defined as products that are purchased and consumed frequently. These products consist primarily of food and beverages as well as personal and household care items. In Europe, these categories account for approximately 15% of total household consumption expenditures.

AiMark collects these data for a large panel of countries through two major marketing research firms, GfK and Kantar. The household panels are designed to be representative of each country’s population using quota-sampling methods. Participating households are instructed to scan all barcode-identified products they purchase, whether bought in physical stores or online. The data do not capture purchases made by institutions (such as canteens, offices, or restaurants) or by non-permanent residents, including tourists.

A.3.2 Agribalyse Data

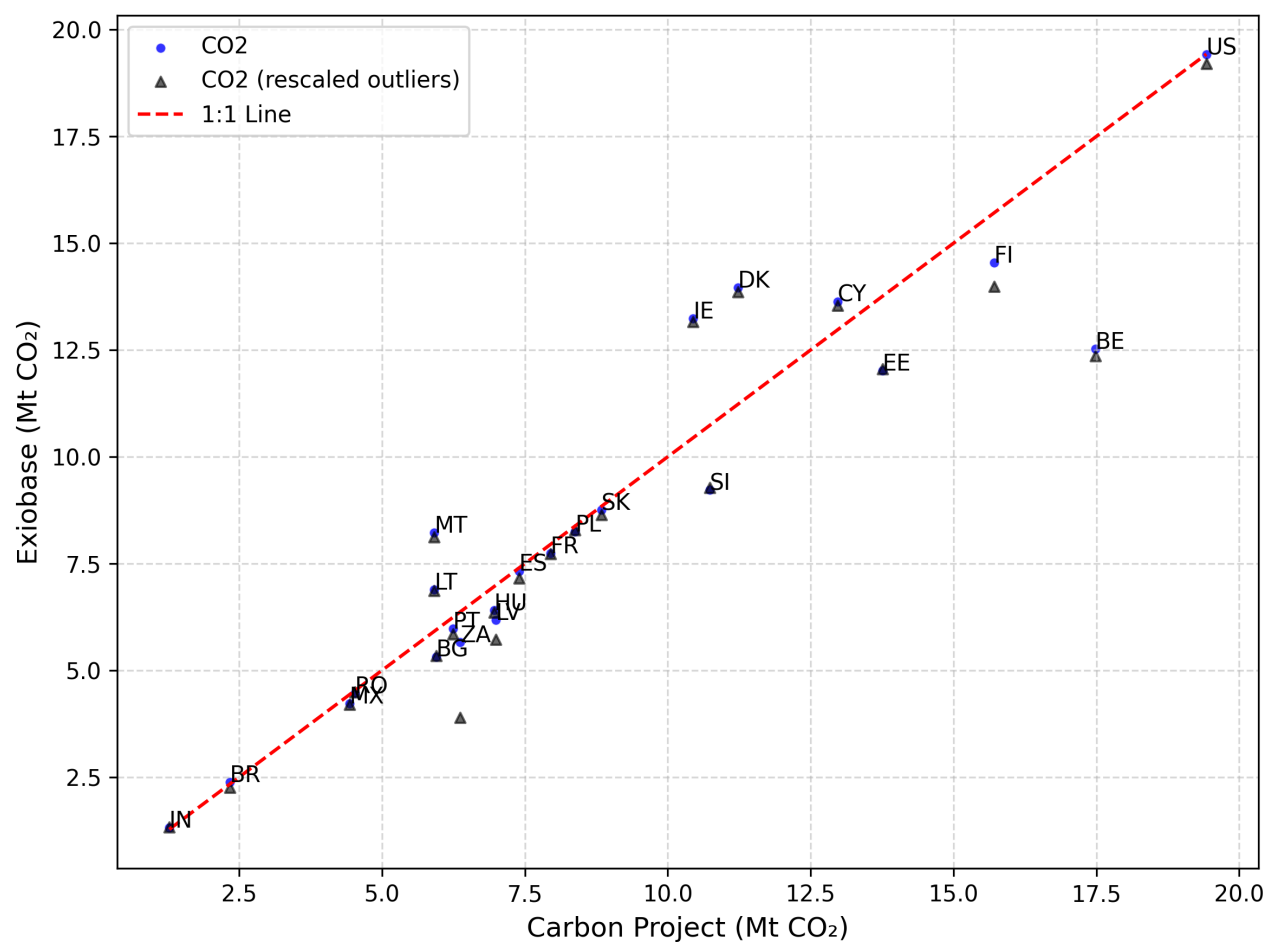
Agribalyse is an open-access database jointly developed and maintained by ADEME, the French Agency for Ecological Transition, and INRAE, the National Research Institute for Agriculture, Food, and the Environment. Agribalyse provides detailed environmental assessments for approximately 2,500 food product categories. These assessments rely on 14 quantitative indicators capturing a broad range of environmental dimensions, including climate change impacts (notably CO₂-equivalent emissions), emissions of fine particulate matter, water consumption, use of fossil resources, land occupation, mineral

and metal depletion, ozone depletion, acidification, ionizing radiation, photochemical ozone formation, as well as terrestrial, marine, and freshwater eutrophication.

For each product category and indicator, the database reports impacts across the full product life cycle, encompassing agricultural production, processing, packaging, transportation, distribution, and consumption. The indicators are constructed by experts from ADEME and INRAE using a Life Cycle Assessment (LCA) framework. The measures are consumption-based and account for both direct and indirect sources of pollution, including emissions generated domestically as well as those embodied in imports.

A key advantage of these LCA-based indicators is their high level of product-level granularity. This allows environmental intensities—particularly carbon intensity—to be characterized at a very fine scale, down to individual barcodes.

Figure A1 : Benchmarking total consumption emissions of CO₂ from Carbon Project and from Ex-iobase



Notes: The figure shows both the raw estimates from Exiobase and those obtained after rescaling outliers. The country most impacted by this rescaling is South Africa whose electricity from coal coefficient is an extreme outlier. The rescaling lowers the estimated footprint with respect to that estimated by the Global Carbon Project.

Figure A2 : UK Total Consumption Emissions Over Time (1996–2017), comparing Defra and Exiobase estimates.

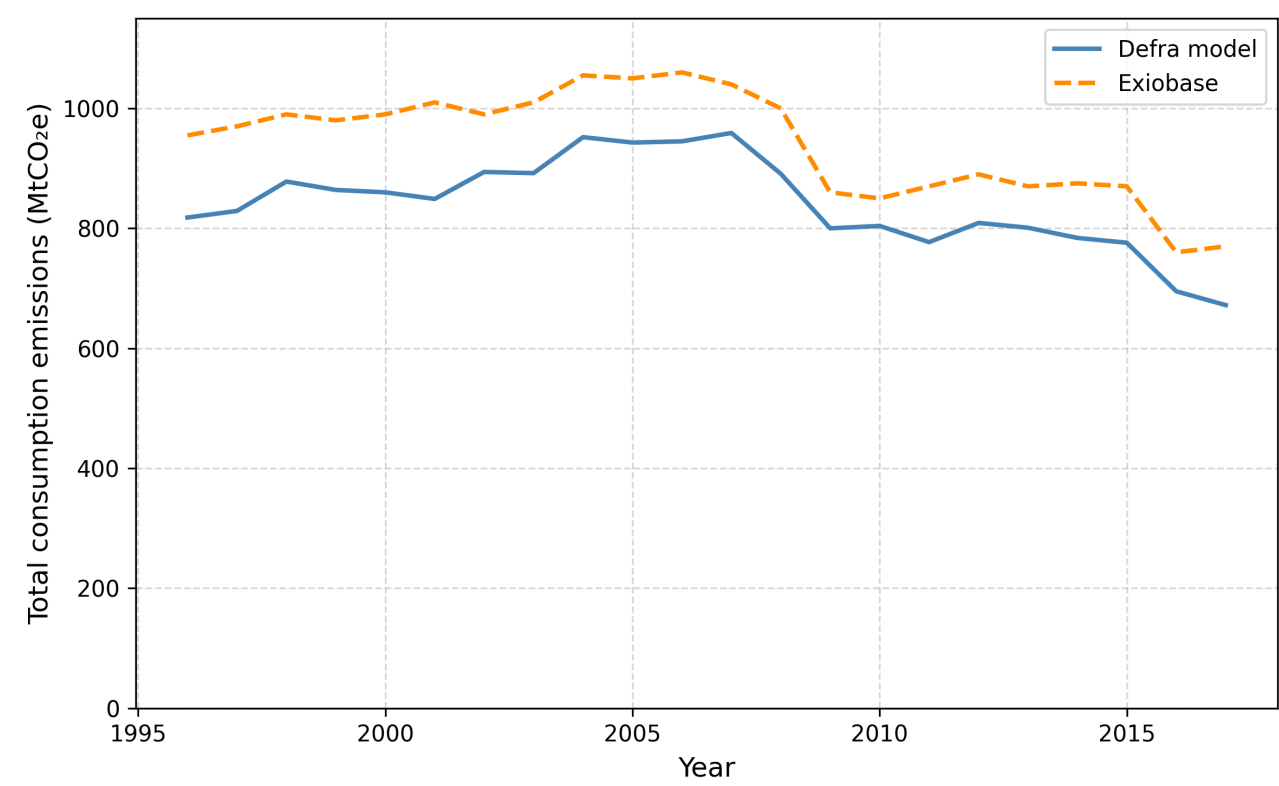


Table A1 : Summary of Original Survey Datasets by Country

Country	Number of Households	Number of Items	Recall Period
European Countries			
Belgium	7,177	197	Weekly to quarterly
Bulgaria	2,982	197	Weekly to quarterly
Cyprus	2,707	197	Weekly to quarterly
Denmark	2,484	197	Weekly to quarterly
Estonia	3,632	197	Weekly to quarterly
Finland	3,551	197	Weekly to quarterly
France	15,797	197	Weekly to quarterly
Greece	3,512	197	Weekly to quarterly
Hungary	9,937	197	Weekly to quarterly
Ireland	5,891	197	Weekly to quarterly
Latvia	3,798	197	Weekly to quarterly
Lithuania	6,103	197	Weekly to quarterly
Malta	3,732	197	Weekly to quarterly
Poland	37,412	197	Weekly to quarterly
Portugal	9,489	197	Weekly to quarterly
Romania	31,336	197	Weekly to quarterly
Slovakia	6,143	197	Weekly to quarterly
Slovenia	3,924	197	Weekly to quarterly
Non-European Countries			
United States	100*	661	Daily to quarterly
India	101,662	327	Monthly to annually
Mexico	19,124	751	Daily to quarterly
South Africa	25,328	752	Biweekly to monthly
Brazil	56,092	4,728	Daily to annually

Notes: * Each US household in our sample is a representative household for a given income percentile.

Table A2 : Number of survey items per large category and country group

Country	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
European countries	63	7	10	10	23	9	15	3	26	5	4	14	7	196
Brazil	61	7	9	8	20	7	11	3	20	3	4	13	5	171
South Africa	60	7	8	7	18	8	11	3	20	5	1	8	4	160
United States	44	6	8	7	18	6	12	3	18	5	4	13	5	149
India	45	5	6	7	14	5	9	3	15	2	3	6	3	123
Mexico	36	5	8	5	14	6	10	3	15	4	2	8	3	119

Notes: This table presents the number of items in the original survey for each country group and large product category. Data for all European countries was obtained from the Household Budget Survey data produced by Eurostat, which already harmonizes survey items across all countries. The numbers refer to the following categories: 1 Food; 2 Alcohol & tobacco; 3 Clothing; 4 Utilities; 5 Furnishings; 6 Health; 7 Transport; 8 Communication; 9 Recreation & culture; 10 Education; 11 Restaurants & hotels; 12 Miscellaneous; 13 Housing.

Table A3 : Share of households reporting no expenditures on fuels or air travel in each country

Country	Town gas & natural gas	Liquefied hydro- carbons	Liquid fuels (other)	Solid fuels	Fuels & lubricants	Passenger transport by air
Belgium	37.9	96.3	68.8	94.3	27.2	93.4
Bulgaria	98.9	82.0	98.7	77.1	59.0	99.7
Cyprus	100	24.1	68.5	47.3	23.5	66.4
Denmark	78.9	96.9	91.1	86.4	39.9	77.7
Estonia	73.1	73.1	95.4	59.6	73.4	92.8
Greece	92.6	75.9	27.7	81.8	33.6	93.1
Spain	59.7	81.3	83.4	94.4	32.6	77.5
Finland	99.9	100	92.8	67.3	45.7	98.7
France	67.8	70.6	85.7	87.5	54.6	96.0
Hungary	22.5	76.1	99.8	63.8	56.5	99.8
Ireland	59.8	97.5	58.2	74.9	25.4	97.0
Lithuania	56.3	80.9	100	96.8	42.6	99.6
Latvia	54.7	64.5	99.6	61.6	64.4	99.5
Malta	100	81.7	99.4	99.1	26.3	91.2
Poland	64.5	72.1	99.8	87.5	49.0	99.6
Portugal	73.6	38.1	97.9	91.0	30.9	96.2
Romania	53.8	66.2	99.9	90.4	72.2	99.9
Slovenia	85.5	89.1	69.0	66.5	45.9	97.5
Slovakia	20.6	95.5	99.9	95.9	42.3	99.8
Brazil	97.2	13.4	98.2	96.6	61.8	98.7
India	99.8	63.1	26.7	30.3	57.8	99.9
Mexico	91.0	100	100	93.5	28.7	85.4
United States	0	31.6	0	26.7	0	0
South Africa	99.6	88.0	97.1	97.8	69.5	97.1
Average	67.0	74.9	82.7	78.4	43.2	90.5

Note: Percentage share of households with no expenditures attributed to a given consumption category associated with direct emissions or aviation in our final data.

Table A4 : Number of emission intensity coefficients per large category and country group

Country	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
Belgium	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Bulgaria	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Cyprus	12	2	4	9	9	3	9	2	11	1	1	7	2	72
Denmark	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Estonia	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Greece	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Spain	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Finland	12	2	4	10	9	3	9	2	11	1	1	7	2	73
France	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Hungary	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Ireland	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Lithuania	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Latvia	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Malta	12	2	4	9	9	3	9	2	11	1	1	7	2	72
Poland	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Portugal	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Romania	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Slovenia	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Slovakia	12	2	4	10	9	3	9	2	11	1	1	7	2	73
Brazil	20	2	5	7	10	3	9	3	12	1	1	6	3	82
India	16	2	4	7	10	3	8	3	8	1	1	4	2	69
Mexico	13	2	4	5	11	3	7	3	8	1	1	6	3	67
United States	15	2	4	7	10	3	9	3	13	1	1	7	2	77
South Africa	20	2	5	7	11	3	8	3	11	1	1	6	3	81

Notes: This table presents the number of emission intensity coefficients in the combined household expenditure surveys-Exiobase data for each country and large product category. The numbers refer to the following categories: 1 Food; 2 Alcohol & tobacco; 3 Clothing; 4 Utilities; 5 Furnishings; 6 Health; 7 Transport; 8 Communication; 9 Recreation & culture; 10 Education; 11 Restaurants & hotels; 12 Miscellaneous; 13 Housing.

B Data construction

B.1 Indirect emission intensities

The steps involved in computing the indirect emission intensities of each Coicop product in each country are as follows.

Match Coicop products to Exiobase products: As explained in the main text, each coicop product may correspond to a single Exiobase product or several Exiobase products. In the latter case, we compute weights for each Exiobase product using aggregate household consumption data available within Exiobase itself. Note that many coicop products may be matched to the same Exiobase product when Exiobase is not as granular as the Coicop nomenclature (e.g. all vegetables fall into a single Exiobase category).

Convert to basic prices: We first convert expenditures in final prices to expenditures in basic prices since Exiobase is in basic prices. We use supply and use tables of each country to determine the share of final price of each product that corresponds to spending in basic price on the product. The supply and use tables also tell us the share of the final price that corresponds to each transport service used in transporting the product and each retail service involved in distributing the product. We apportion those shares to the corresponding transport and retail sectors in Exiobase. This implies that the indirect emission coefficients involve all steps from raw material extraction to its distribution. After conversion to basic prices, we determine the share of each euro spent on product j that is sourced from different countries. These two steps yields a demand vector $\tilde{y}_{c(h),j}$, which represents the demand induced in basic prices by one euro of final-price spending on coicop product j in country $c(h)$, accounting for imports of product j in all countries as well as the transport and retail sectors.

Calculate the footprint: We then compute:

$$i_{c(h),j} = gSL\tilde{y}_{c(h),j} \quad (10)$$

where S is the Exiobase matrix of greenhouse gas emission coefficients (this is the matrix that we screened for outlier coefficients), L is the Leontieff inverse, and g is a vector of global warming potentials, which converts each greenhouse gas emission to a CO₂ equivalent. $i_{c(h),j}$ is then in units of $CO_2e/euro$. Figure A3 plots the distribution across countries of the indirect emission intensity coefficients for the items with the largest emission intensity in each large category. Meat of bovine animals and electricity are the coefficients with the highest indirect emission intensity (respectively 2.5kg and 4.7kg per CO₂ on average). There is considerable variation across countries for the emission intensity of electricity, reflecting differences in the sources of fuels used to generate electricity: both South Africa and India for example rely heavily on coal.

B.2 Direct emissions

To construct direct emissions, the challenge is to recover an emission coefficient for the combustion of each fuel in monetary unit for each country in our dataset, since this is not available in Exiobase. The UN Energy Statistics (which can be queried on the UN Data Portal) compiles statistics of each country's total consumption (in physical units) of each source of energy, and for most sources, it also includes total consumption by households. When total consumption by households was not available, we inferred by using the share of household consumption in total consumption as reported in Exiobase. We then converted these values (total household consumption of each fuel in physical units) into emissions of each greenhouse gas using coefficients published by the US Environmental Protection Agency (GHG Emission Factors dataset). We then used a correspondence between COICOP and SIEC nomenclature of fuels (used by the UN Data and the EPA factors data) to aggregate total emissions by households for each fuel category in COICOP. We then convert this to a direct emission factor by dividing by total household consumption in the consumer expenditure datasets.

The distribution of the resulting direct emission intensity coefficients is show in Figure A4. We note that our method of estimating direct emissions is imperfect as it divides quantities from two very different datasets (UN aggregate energy statistics and household consumption survey) to obtain an implicit price. When quantities are small, this method can be very noisy, which is why we have removed solid fuels from the figure. We see that liquefied hydrocarbons (e.g. butane, propane) has significant outliers, which are also due to the errors that arise when dividing by small quantities.

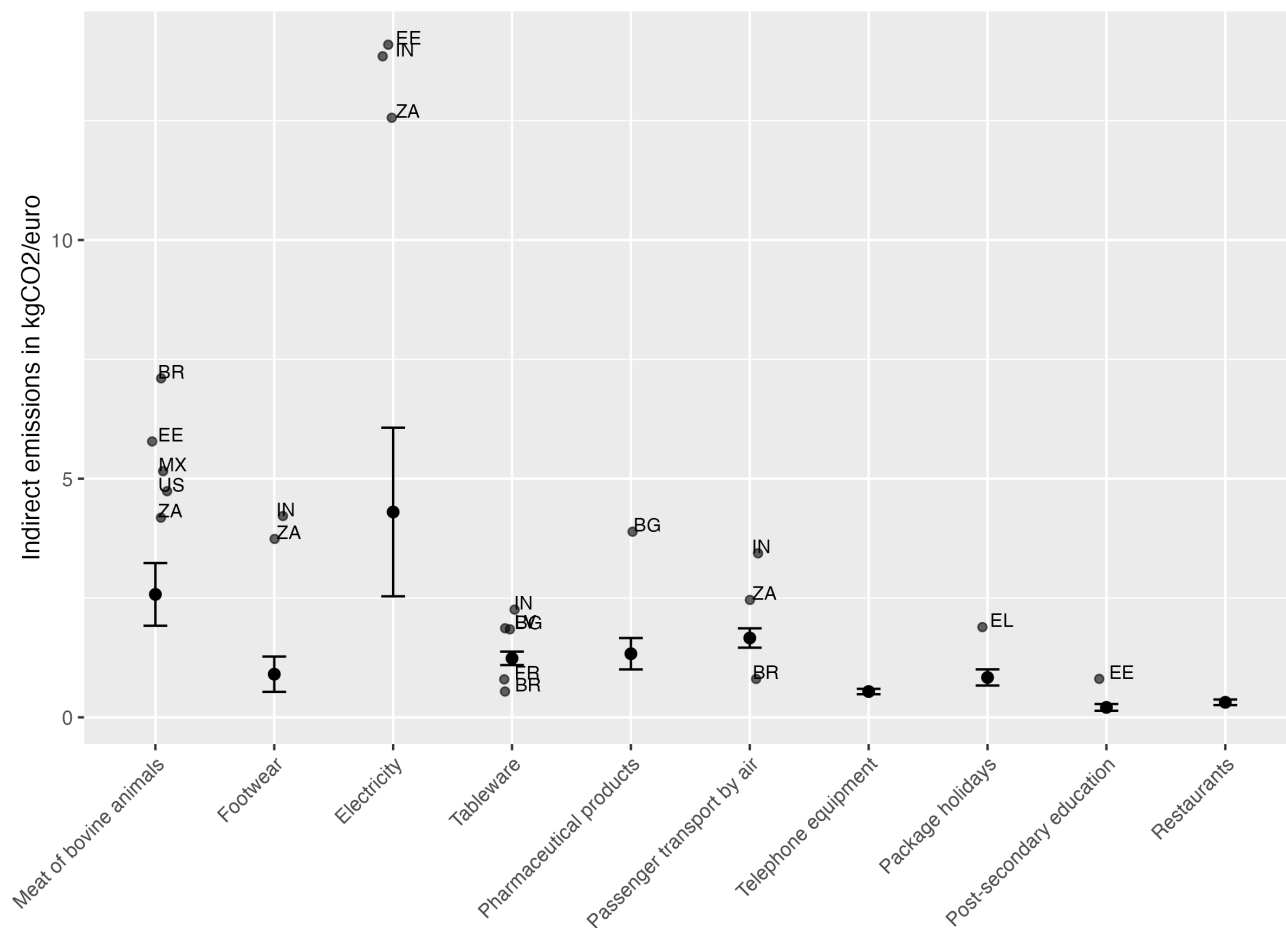
B.3 Household emissions

Table A5 documents the average expenditure, average per capita footprint and fifth and ninety-fifth percentile of the per capita footprint for each country in our dataset. Figure A5 plots the distribution across countries of the average share of expenditure and the average intensity coefficients for each broad coicop category.

B.3.1 Benchmarking GHG household expenditure elasticities with other studies

Figure A6 shows how our estimates of each country's household-level GHG elasticity with respect to expenditure compares to other estimates in the literature. These estimates were compiled in the meta-analysis by Chancel (2022). Most come from a compilation of the literature by Pottier (2022) or are calculated by the author using data from Bruckner et al. (2022) (using GTAP and the World Bank's expenditure data by decile). We see that most estimates in the literature cover CO₂ only instead of all greenhouse gases, whereas all our estimates cover all greenhouse gases. This difference can explain why estimates from the literature tend to be higher than ours, since non-CO₂ GHG more comprehensively capture emissions from the food sector, the consumption sector with the lowest elasticity. When GHG elasticity estimates are available, our own estimates are closely aligned.

Figure A3 : Distribution of key indirect emission intensity coefficients



Notes: This figure shows the means, their 95% confidence intervals and outliers of indirect emission coefficients for selected products. The products selected are the most emitting within each coicop 2 broad category. Indirect emission coefficients take into account all emissions from extraction of raw materials to transport and distribution of the final product.

Figure A4 : Distribution of direct emission intensity coefficients from the combustion of fuels consumed by households representing means and their confidence interval

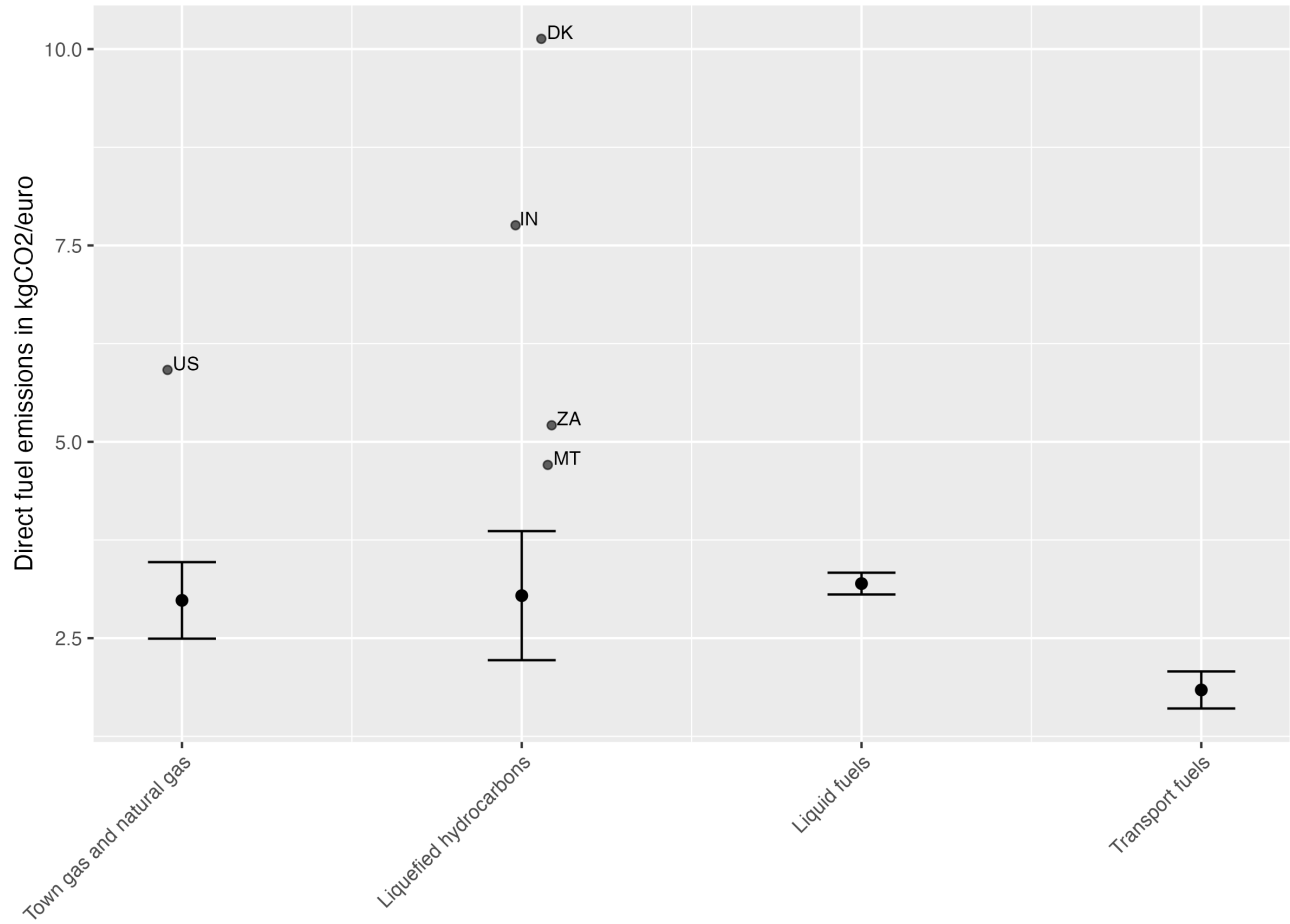
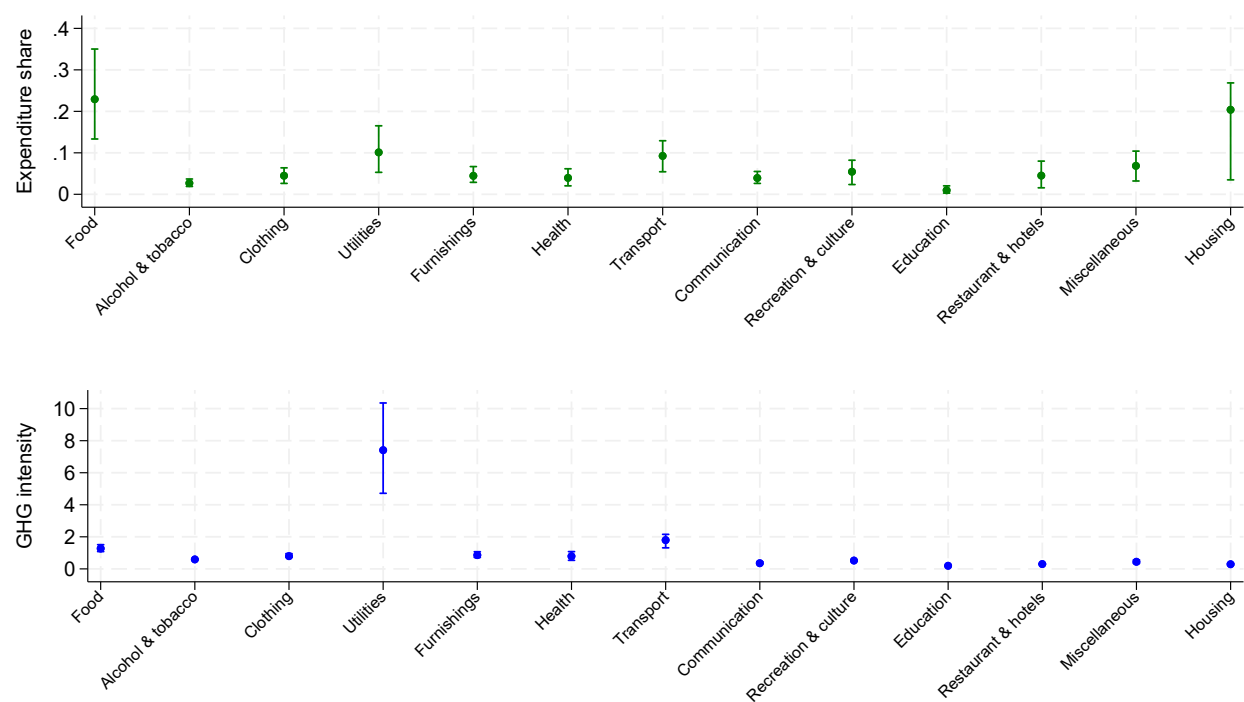


Figure A5 : Expenditure and GHG Intensity across Countries and broad Categories



Notes: This figure shows the between-country distribution of each category's mean share of total household expenditure (top panel) and GHG intensity (GHG emissions per unit of expenditure; bottom panel). In both panels, the center dot represents the average of country-level means, and the interval is the 90% confidence interval.

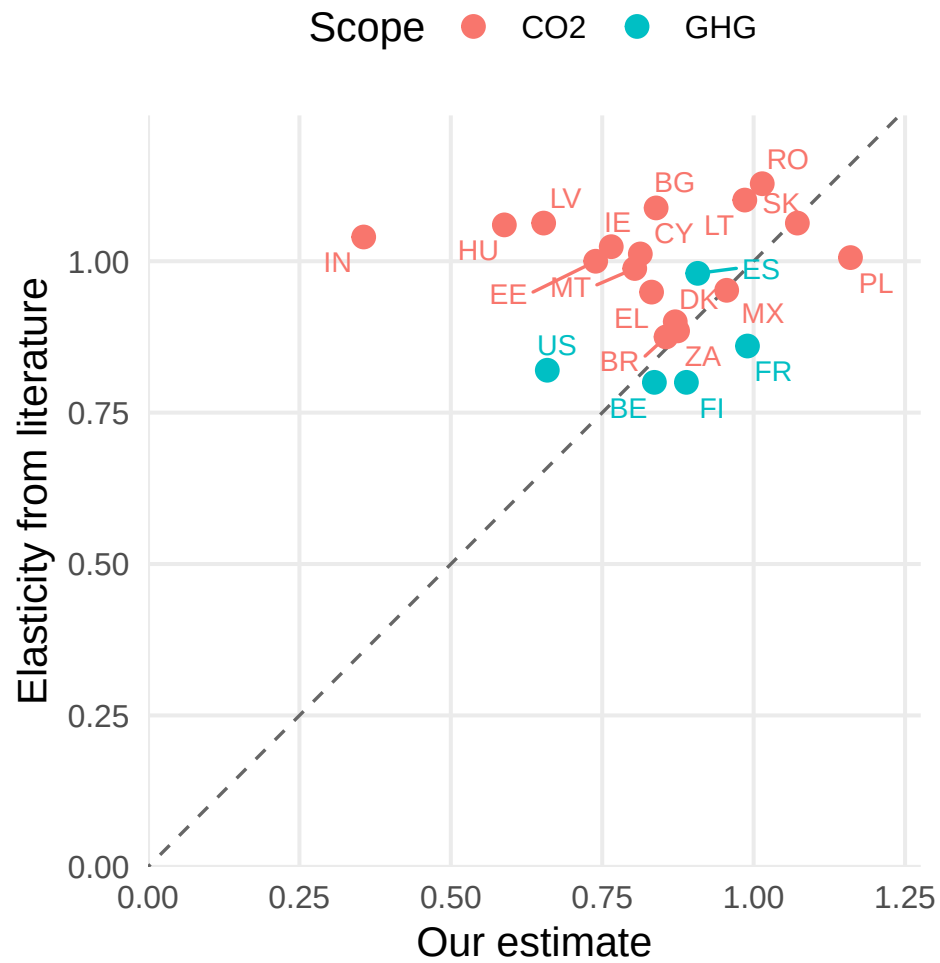


Figure A6 : Comparison of our estimates of the elasticity of GHG with respect to total expenditures to the estimates used in the meta-analysis by Chancel (2022). Note that the literature estimates are also with respect to expenditures, but some estimates cover only CO₂ instead of all GHG (indicated by Scope). All our own estimates cover all GHGs.

Table A5 : Expenditures and GHG emissions summary

Country	Expenditures	Direct Emissions share	CO2e, mean	CO2e, p5	CO2e, p95
Belgium	17985	.25	11.8	4.4	23.2
Bulgaria	4928	.14	10.9	2.9	28.4
Cyprus	20679	.13	18.7	7.5	36.2
Denmark	17281	.16	14.7	4.6	37.4
Estonia	5898	.18	13.4	4	29.2
Greece	14677	.22	11.8	4.4	25
Spain	15446	.19	8.5	2.5	18.3
Finland	16271	.17	12.7	3.6	26.2
France	16130	.26	7.6	1.6	18.1
Hungary	7550	.34	12.4	4.9	24.5
Ireland	16444	.31	11.6	3.6	24.9
Lithuania	7512	.12	10.8	2.3	23.1
Latvia	5991	.26	15.6	3.8	35.6
Malta	12542	.08	13	4.8	26.6
Poland	7681	.2	16.5	2.5	50.1
Portugal	11675	.28	8.5	1.6	24.3
Romania	4648	.2	5.4	1.2	15.8
Slovenia	13413	.32	12.2	3.9	25.7
Slovakia	7186	.17	21.5	2.8	56.3
Brazil	2811	.26	2.7	.3	7.7
India	441	.46	1.7	.7	3.2
Mexico	2238	.24	2.6	.4	7.4
United States	18141	.39	14.6	10.7	19.1
South Africa	3652	.09	5.1	.6	18.6

Note: all variables are in per capita terms. The expenditure variable is in Euros, the CO2 variables correspond to CO2 equivalents in tons.

C Aimark-Agribalyse

C.1 Cleaning of Aimark barcodes

We import the raw barcode file from the Aimark data and retain the text description of the barcode and the barcode itself. Aimark’s barcode description embeds multiple labeled facets inside a single string—each facet begins with a French label and a numeric code (for instance: “Quel Groupe (2) : ...”, “Conservation (12) : ...”). In order to match each barcode to an Agribalyse category we need to keep facets with the most relevant information about the product, and discard descriptions of it that would only act as noise when matching the products. To do so we parse these facets into separate variables using a common pattern:

1. Search the description for the start label (e.g. “Quel Groupe (2) :”).
2. If present, take the substring that follows the label; if not present, leave the facet empty.
3. Trim the facet to discard trailing qualifiers or notes.

This procedure is applied to a series of facets that together summarize the product’s attributes: **Quel Groupe (2)** (high-level group indicator), **Conservation (12)** (storage/keeping conditions such as ambient, chilled, frozen), **Présentation (34)** (packaging or presentation format), **A Base de (40)** (principal ingredient or base), **Quel Légume (41)** (specific vegetable), **Quel Produit (44)** (specific product type), **Quelle Boisson (47)** (beverage type), **Quel Fromage (75)** (cheese type), **Quel Type (80)** (subtype qualifier), **Recette (90)** (recipe or style variant), **Quel Jambon (100)** (ham type), **Type de Viande (230)** (meat type), and **Type de Plat (250)** (prepared-dish type). Each facet is created only if its label is found; otherwise it is left empty.

We then form a single cleaned product description by concatenating the extracted facets in a fixed order. This standardizes the form across entries and keeps semantically informative tokens (ingredient, product type, presentation, conservation). The original raw description is retained in parallel.

Because Aimark also contains non-food merchandise, we exclude entries whose extracted *Quel Groupe (2)* facet clearly indicates non-food domains (e.g. hygiene, textiles, parapharmaceuticals, household cleaning, insecticides, batteries). This ensures that the resulting dataset is restricted to genuine food items compatible with Agribalyse.

We drop observations where the synthesized cleaned string is empty or degenerate (e.g. a lone “.”). We then retain only the fields necessary for matching: the cleaned description, the barcode, and the original barcode description.

We produce two files out of this procedure:

1. A *full cleaned panel* in Stata format, preserving one row per barcode with both original and cleaned descriptions. This serves as an audit trail and can be merged back to transactional data via the barcode.
2. A *uniqued list of cleaned descriptions containing 3017 items*, in CSV format, where duplicates are dropped at the level of the cleaned string. This avoids redundant candidate pairs during semantic matching.

In sum, the procedure converts heterogeneous, facet-encoded barcode descriptions into standardized, food-only strings that emphasize discriminative attributes. These cleaned strings form the reliable textual substrate for the subsequent semantic match to Agribalyse and HBS.

C.2 Aimark-Agribalyse-HBS match

Our objective is to match the Aimark barcodes to two datasets: (i) Agribalyse product items and (ii) HBS product categories. To achieve this, we construct a crosswalk from the cleaned Aimark barcode descriptions to the two datasets using a Natural Language Processing approach.

First, we combine the cleaned Aimark barcode descriptions from Aimark into a single corpus and estimate TF-IDF weights. TF-IDF (term frequency-inverse document frequency) assigns higher weight to tokens that are frequent within a given description but relatively rare across the corpus, and lower weight to tokens that occur in nearly all descriptions. Tokens that appear almost everywhere in this corpus (the bottom 1.5% of the IDF distribution) are deemed uninformative for matching and are removed.

Before removing frequent words, each Aimark string is lightly normalized: tokens are lower-cased, extracted with a word-boundary regex, and de-duplicated while preserving the original order (so repeated brand or size tokens do not artificially inflate similarity). If all tokens in a string would be removed by the frequent words filter, the method falls back to the pre-filtered token set to avoid producing empty strings. Cleaning is applied to Aimark only; Agribalyse item names are left intact to preserve their official labeling. For auditability we retain the original Aimark text alongside its cleaned version. Importantly, the Aimark input that enters the matching procedure is not the raw barcode description but the clean set of barcode descriptions created in the preprocessing step described above.

Second, we match Aimark products to Agribalyse items using LinkTransformer’s French semantic matcher (`dell-research-harvard/lt-wikidata-comp-fr`). This model encodes each string into a sentence embedding and scores candidate pairs by cosine similarity. We generate candidate links between cleaned Aimark strings and Agribalyse items, rank them by similarity, and keep those above a fixed acceptance threshold of 0.55. The procedure does not force one-to-one matches: multiple Aimark strings may map to the same Agribalyse item, which is desirable when retailer phrasing varies around a common underlying product.

Third, we merge this Aimark-Agribalyse crosswalk to HBS food categories using a second LinkTransformer model tuned to UN-style label spaces (`dell-research-harvard/lt-un-data-fine-coarse-fr`). The same embedding-and-similarity logic applies: each incoming label is matched to the closest HBS label(s) (which has been translated into French).

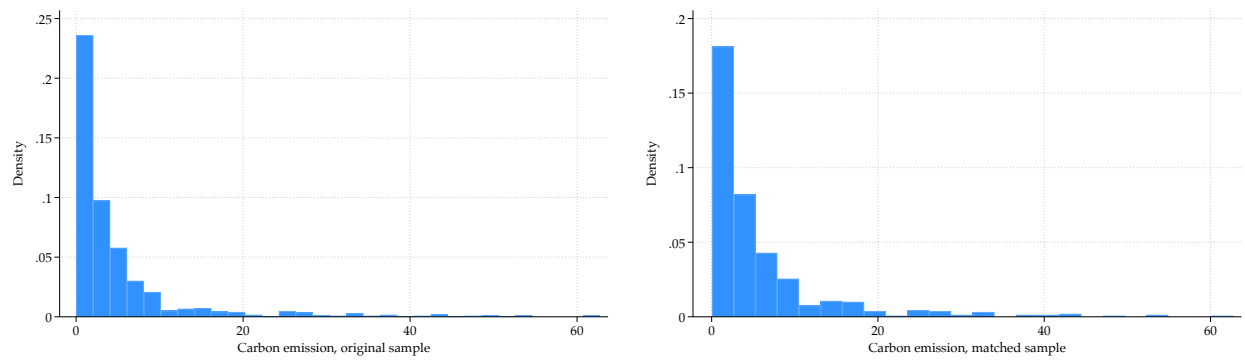
The resulting crosswalk is a table with four essential pieces of information per retained product: the cleaned Aimark description (with the original in a parallel field for traceability), the matched Agribalyse item, the matched HBS label.

Two hyperparameters govern the precision of the match: the IDF percentile used to define domain stop-words (set to 1.5%) and the similarity threshold for accepting Aimark-Agribalyse matches (set to 0.55). We set the parameters heuristically to maximize the quality of the match.

This procedure yields a match to 870 distinct Agribalyse product categories and 65 HBS categories, providing broad coverage of the food domain and ensuring consistency between detailed product-level

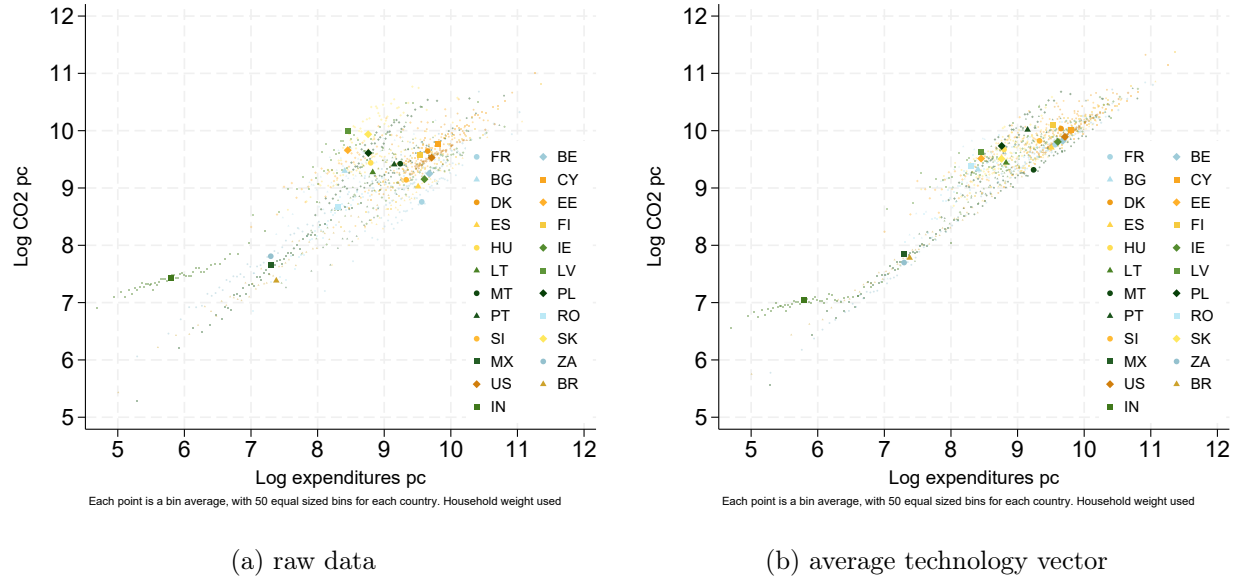
data and standardized consumption taxonomies. Importantly, the distribution of CO₂ emission intensities in the full Agribalyse dataset does not substantially differ from the distribution of CO₂ emission intensities in the matched data, as is shown in A7.

Figure A7 : Distribution of CO2 intensity coefficients in original and matched samples



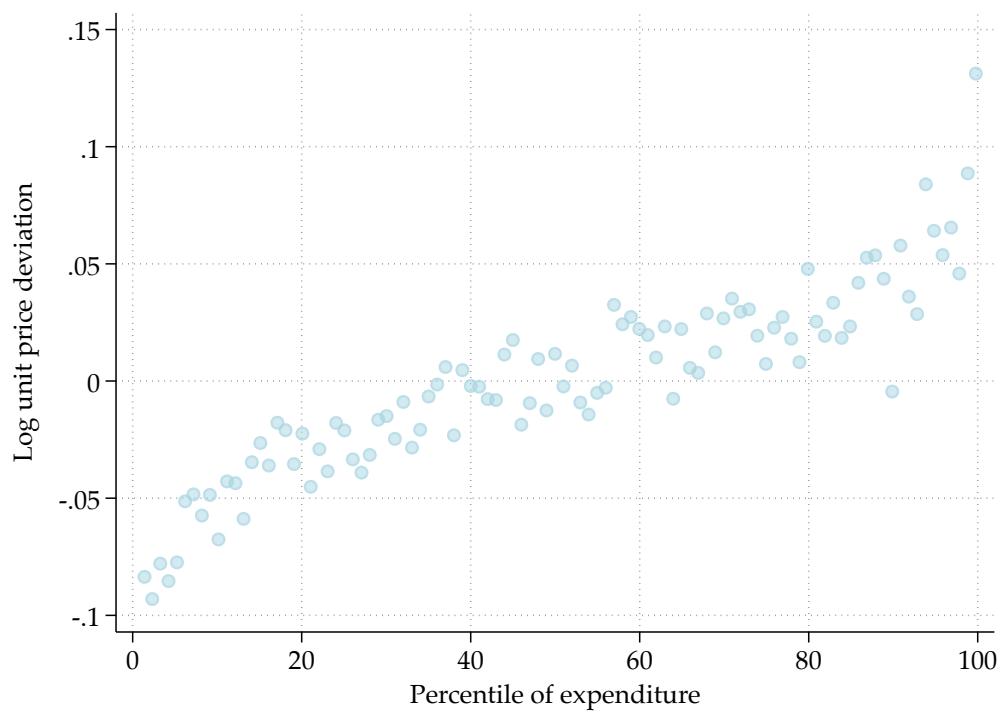
D Additional figures and tables

Figure A8 : GHG Engel Curves, including emissions from housing capital



Notes: This figure plots log GHG emissions per capita against log expenditures per capital for all countries in our sample, where we include emissions from housing capital formation. Panel (a) plots emissions obtained by combining household expenditure surveys and country-specific emission coefficients, Panel (b) uses the same average emission coefficient for all countries, see the text for more details.

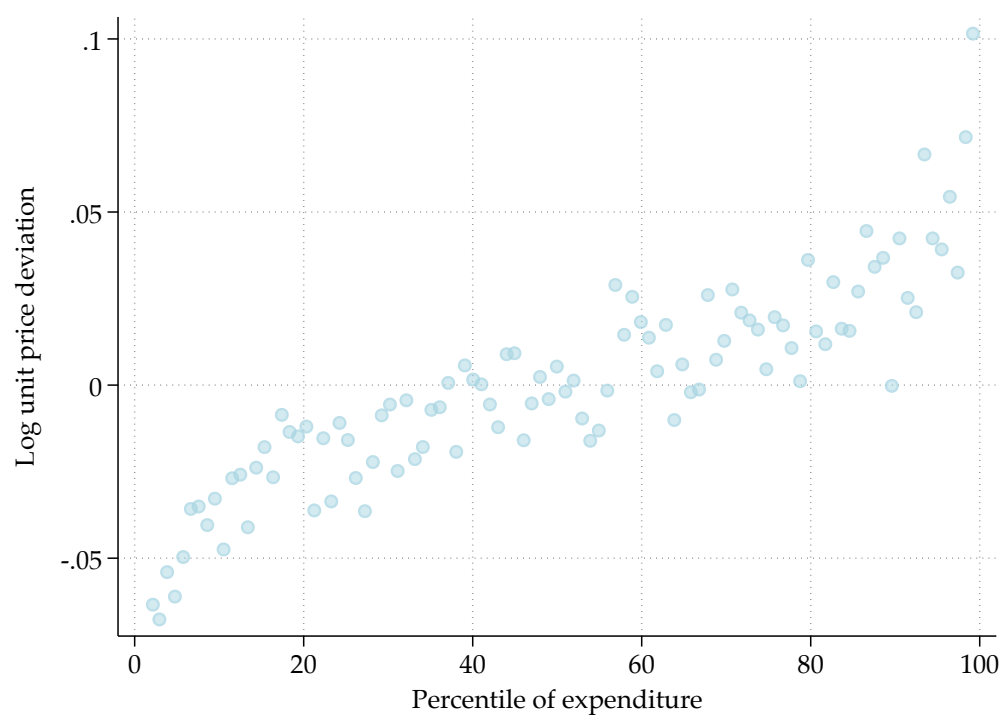
Figure A9 : Unit prices over the household expenditure distribution



Notes: This Figure

plots the average log deviation in unit prices from the average price within one of the 65 HBS category for each percentile of the distribution of the household total food expenditures in France, using the Aimark dataset.

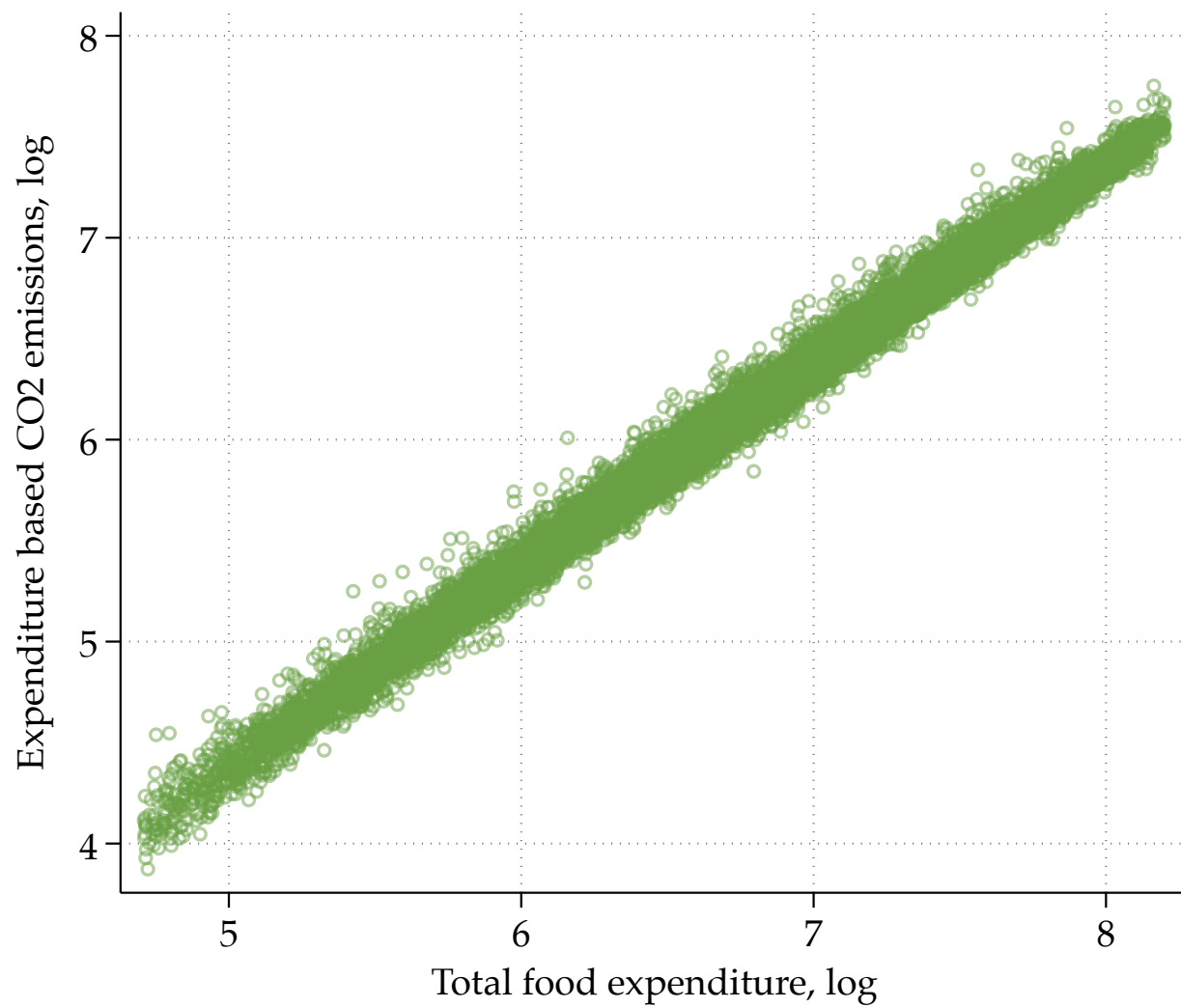
Figure A10 : Unit prices of the household expenditure distribution, with finer Aimark-agribalyse product categories



Notes: This figure

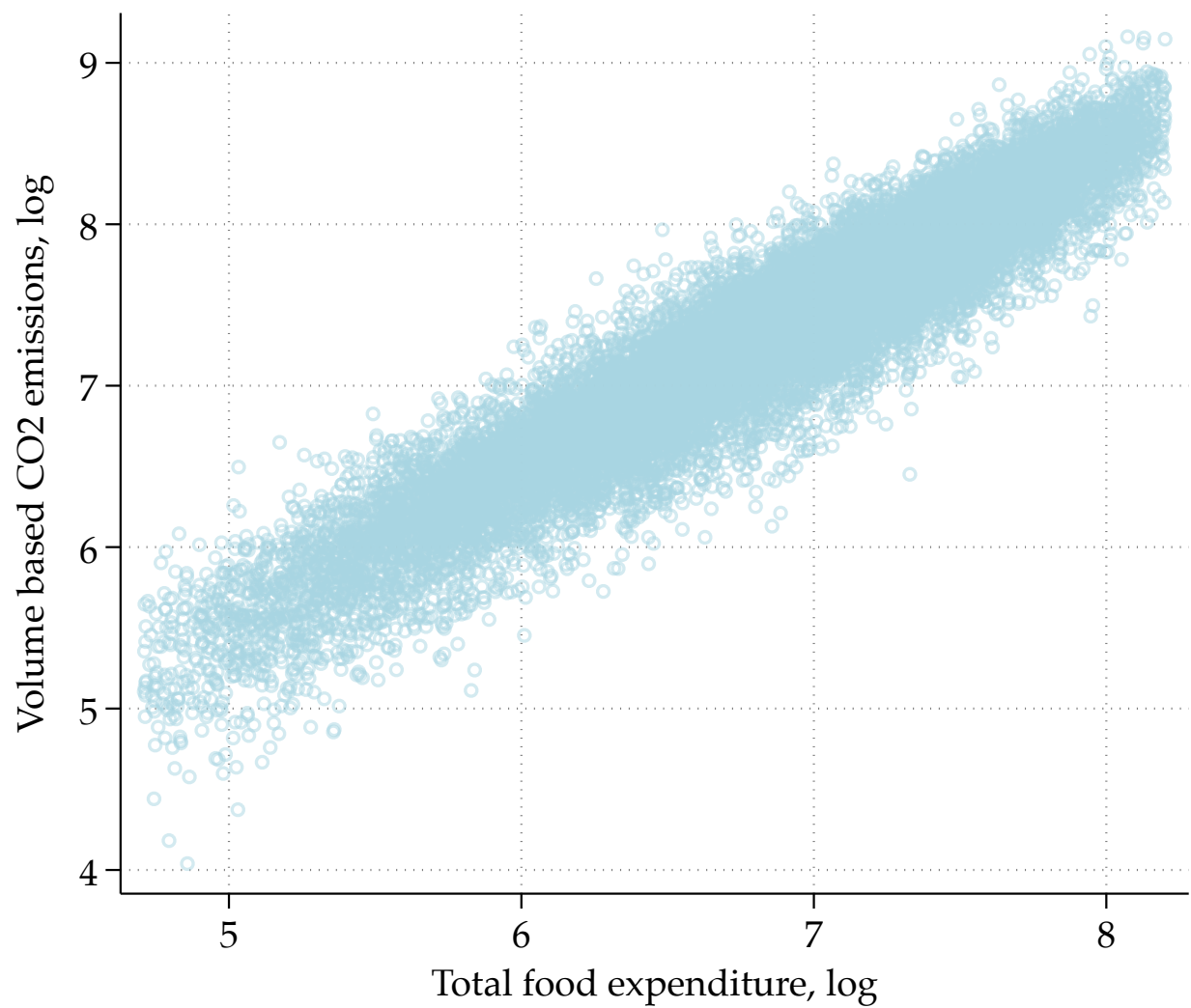
plots the average log deviation in unit prices from the average price within the 870 Aimark-Agribalyse categories for each percentile of the distribution of the household total food expenditures in France, using the Aimark dataset.

Figure A11 : Emissions as a function of total expenditures, expenditure definition using coarse categories



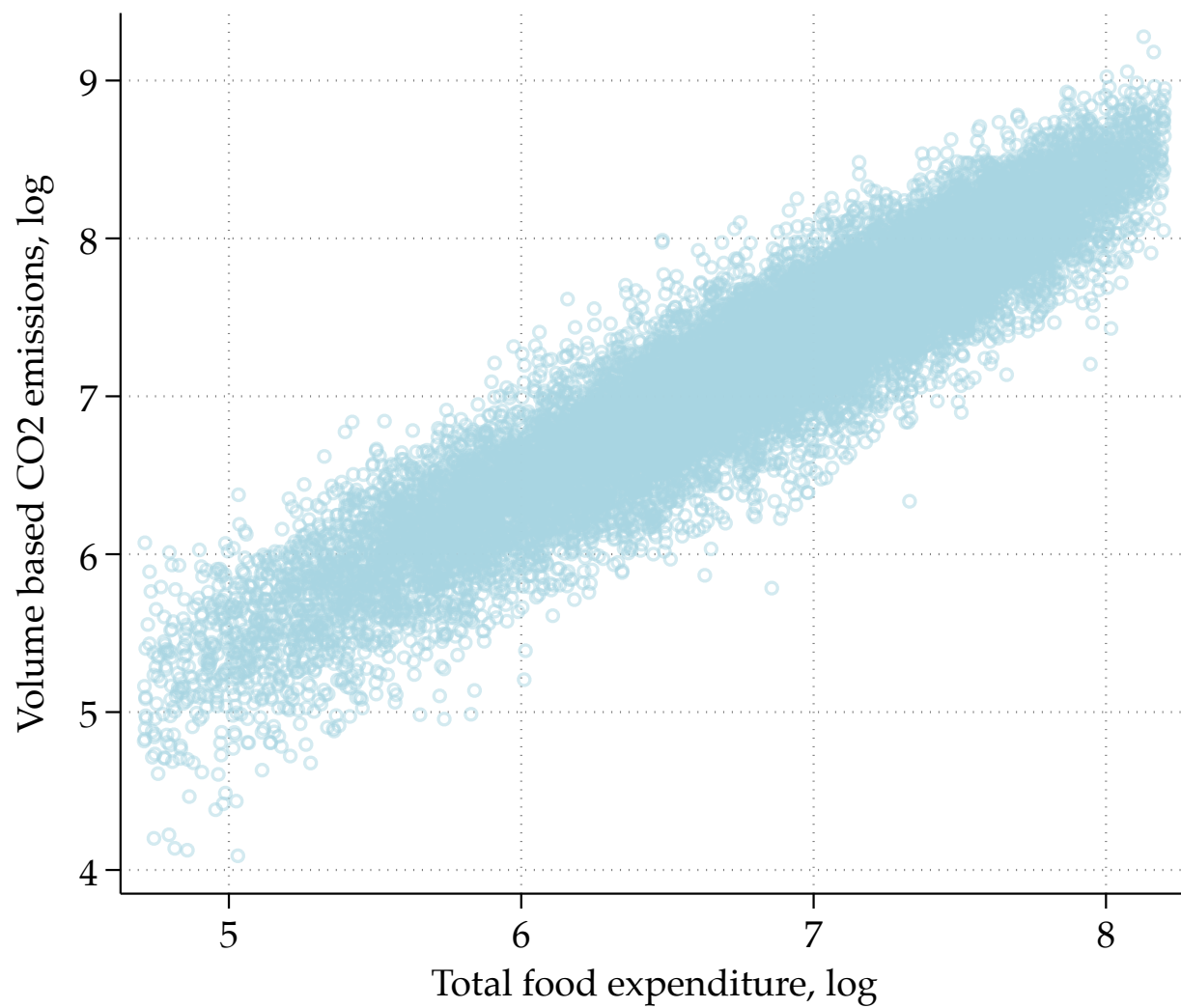
Notes: Variation is at the household level.

Figure A12 : Emissions as a function of total expenditures, volume definition using coarse categories



Notes: Variation is at the household level.

Figure A13 : Emissions as a function of total expenditures, volume definition using fine categories



Notes: Variation is at the household level.

Table A6 : Anatomy of CO2 Engel curves across 13 product categories, MICs

Product category	GHG Share	Exp. Share	GHG Intensity	GHG Elasticity	Exp. Elasticity	Between	Within	Global Elasticity
Utilities	0.35	0.09	9.40	0.53	0.80	0.44	-0.15	0.74
Food	0.34	0.34	1.77	0.60	0.67	0.36	-0.04	0.74
Transport	0.12	0.10	1.67	1.08	0.86	0.16	0.04	0.74
Clothing	0.04	0.06	1.04	0.31	0.38	0.03	0.00	0.74
Furnishings	0.03	0.05	0.96	0.73	0.78	0.04	0.00	0.74
Health	0.03	0.04	1.09	0.28	0.36	0.01	0.00	0.74
Housing	0.02	0.12	0.22	1.34	1.33	0.05	0.00	0.74
Miscellaneous	0.02	0.06	0.50	0.80	0.88	0.03	0.00	0.74
Communication	0.01	0.04	0.47	0.84	0.99	0.02	0.00	0.74
Recreation & culture	0.01	0.03	0.57	0.99	1.07	0.02	0.00	0.74
Alcoholic beverages	0.01	0.02	0.46	0.80	0.76	0.01	0.00	0.74
Restaurants & hotels	0.01	0.03	0.29	-0.34	-0.32	0.00	0.00	0.74
Education	0.00	0.01	0.23	-1.16	-1.15	0.00	0.00	0.74

This table presents the broad-category decomposition for Brazil, India, Mexico, Romania and South Africa, using a carbon-intensity vector averaged equally across countries in that group and the same decomposition definitions as the main table. All category elasticities are estimated against total expenditure on a common sample within each category. Contributions are normalized before rounding.

Table A7 : Anatomy of CO2 Engel curves across 13 product categories, HICs

Product category	GHG Share	Exp. Share	GHG Intensity	GHG Elasticity	Exp. Elasticity	Between	Within	Global Elasticity
Utilities	0.41	0.10	5.65	0.29	0.46	0.17	-0.07	0.66
Food	0.16	0.20	0.80	0.42	0.40	0.06	0.00	0.66
Transport	0.15	0.09	1.65	2.94	2.91	0.39	0.00	0.66
Housing	0.07	0.22	0.29	1.16	1.16	0.07	0.00	0.66
Miscellaneous	0.04	0.07	0.47	1.85	1.94	0.06	0.00	0.66
Recreation & culture	0.03	0.06	0.47	2.04	1.98	0.06	0.00	0.66
Furnishings	0.03	0.04	0.82	1.53	1.75	0.05	-0.01	0.66
Health	0.03	0.04	0.80	1.45	1.70	0.05	-0.01	0.66
Clothing	0.03	0.04	0.62	2.37	2.37	0.06	0.00	0.66
Restaurants & hotels	0.02	0.05	0.33	3.44	3.44	0.06	0.00	0.66
Alcoholic beverages	0.02	0.03	0.58	1.42	1.42	0.02	0.00	0.66
Communication	0.01	0.04	0.23	0.91	0.90	0.01	0.00	0.66
Education	0.00	0.01	0.21	3.06	3.06	0.01	0.00	0.66

This table presents the broad-category decomposition for the remaining European countries and the United States, using a carbon-intensity vector averaged equally across countries in that group and the same decomposition definitions as the main table. All category elasticities are estimated against total expenditure on a common sample within each category. Contributions are normalized before rounding.

Table A8 : Decomposition of GHG Engel Curves, including Emissions from Building Construction

Product category	GHG Share	Expenditure Share	GHG Intensity	GHG Elasticity	Expenditure Elasticities	Contribution Between	Contribution Within
Utilities	.35	.1	7.61	.7	.87	.28	-.02
Food	.2	.24	1.29	.56	.62	.13	-.01
Housing	.18	.2	1.21	1.23	1.22	.25	0
Transport	.12	.09	1.8	1.35	1.27	.18	.01
Clothing	.03	.05	.8	.8	.87	.02	0
Furnishings	.03	.05	.86	.91	.98	.02	0
Miscellaneous	.02	.07	.45	1.11	1.22	.03	0
Recreation & culture	.02	.05	.52	1.34	1.37	.03	0
Health	.02	.04	.79	.74	.9	.02	0
Restaurants & hotels	.01	.04	.3	1.81	1.82	.02	0
Alcohol & tobacco	.01	.03	.59	.71	.71	.01	0
Communication	.01	.04	.36	.83	.95	.01	0
Education	0	.01	.19	.86	.87	0	0

Notes: This table presents the share of worldwide GHG emissions accounted for by the thirteen product categories, along with their expenditure share, GHG intensity (kg of GHG per euro), GHG elasticity ($d \log e_k / d \log c$), and expenditure elasticity ($d \log c_k / d \log c$). Categories are ordered by GHG share.

Table A9 : Price expenditure elasticity, with consumption categories

	Log price	Log price	Log price
Log expenditure	0.031*** (0.000)	0.039*** (0.000)	0.054*** (0.001)
HBS FE	<i>No</i>	<i>No</i>	<i>Yes</i>
Agribalyse FE	<i>No</i>	<i>Yes</i>	<i>No</i>
Aimark FE	<i>Yes</i>	<i>No</i>	<i>No</i>
Observations	2205150	2205166	2205175
Adj. R^2	0.808	0.708	0.309

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10 : Elasticity of emissions with respect to total food expenditures

Emissions definition:	Coarse, euros	Coarse, kg	Fine, kg
Log expenditure	0.997*** (0.001)	0.984*** (0.003)	0.987*** (0.003)
Observations	17808	17808	17808

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$