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Documents de travail

N° 2024-01– Février 2024

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Mesurer pour comprendre

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2024/01

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12 février 2024

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# Les défis de la mesure de la distribution des empreintes carbone : le rôle de l'hétérogénéité des produits et des prix

En raison du manque de données adéquates sur les caractéristiques des ménages, leur panier de consommation détaillé et le contenu en carbone de chaque article de ce panier, la distribution de l'empreinte carbone par groupe de ménages au sein d'un pays est régulièrement calculée à l'aide des données de consommation, en partant du principe que l'empreinte carbone d'une catégorie de produits est proportionnelle aux dépenses consacrées à ce produit. Nous explorons ici les limites de cette hypothèse de proportionnalité. Nous fournissons un cadre systématique pour discuter de l'écart entre l'empreinte carbone réelle et l'empreinte carbone imputée par les dépenses, un cadre valable pour tout type d'empreinte. Nous montrons que deux canaux peuvent fausser la distribution de l'empreinte carbone : l'hétérogénéité des prix payés et l'hétérogénéité de l'intensité carbone des produits achetés. Nous nous appuyons sur les données de l'enquête sur le budget des ménages français pour illustrer le fonctionnement et l'interaction de ces canaux, et nous utilisons les huiles de cuisson comme étude de cas de l'interaction des deux canaux. Nous constatons que les ménages plus aisés paient des prix plus élevés. En raison de l'hétérogénéité des prix, l'empreinte carbone tend à être surestimée pour les revenus les plus élevés et sous-estimée pour les revenus les plus faibles. Nous utilisons également la consommation d'huiles de cuisson comme étude de cas plus approfondie de l'hétérogénéité de l'intensité de carbone. Ce cas montre qu'il peut conduire à un résultat similaire à l'hétérogénéité des prix.

Mots clés : empreinte carbone ; émissions de GES ; inégalités ; consommation des ménages ; enquêtes sur les dépenses ; redistribution

Code JEL: D12, D30, D31, Q56, Q57, R20

# Challenges in measuring the distribution of carbon footprints : the role of product and price heterogeneity

Due to the lack of adequate data with information on household characteristics, their detailed consumption basket and the carbon content of each item in this basket, the distribution of the carbon footprint by households groups within a country is regularly computed using consumption data with the assumption that the carbon footprint from a product category is proportional to the spending on that product. Here, we explore the limitations of this proportionality assumption. We provide a systematic framework for discussing the gap between the true carbon footprint and the carbon footprint imputed with spending, a framework which is valid for any type of footprint. We show that two channels can bias the distribution of the carbon footprint: the heterogeneity in prices paid and the heterogeneity in the carbon intensity of products purchased. We rely on French household budget survey data to illustrate how these channels operate and interplay, and use cooking oils as a case study of the interplay of the two channels. We find that wealthier households pay higher prices. Because of the price heterogeneity, the carbon footprint tends to be overestimated for top income and underestimated at the bottom. We also use consumption of cooking oils as a more-in depth case study of the carbon intensity heterogeneity. This case shows that it can lead to an outcome similar to price heterogeneity.

Keywords: carbon footprint; GHG emissions; inequality; household consumption; expenditure surveys; distribution

JEL Code: D12, D30, D31, Q56, Q57, R20

# 1 Introduction

The carbon footprint is a standard measure to assess the sustainability of consumption, by measuring the amount of greenhouse gases (GHG) that can be linked to that consumption. The carbon footprint thus refers to the amount of GHG emitted upstream, along the production chain, to produce the goods and services consumed (consumption-based emissions).[1] This consumption-based perspective has been first introduced and applied at the national level, in debates about the respective contribution of countries to climate change (Munksgaard and Pedersen, 2001; Bastianoni et al., 2004). It is now widely applied to other entities like households (among scores of studies, see Hubacek et al. (2017) at the world level, Ivanova and Wood (2020) at the European union level, or Pottier et al. (2020); Malliet (2020) for France), or even territories or cities (Moran et al., 2018; Heinonen et al., 2020). The development of Multi-Regional Input Output (MRIO) models helped to make it a standard tool for analysis of ecological economics or industrial ecology, and an important pillar to guide the ecological transition.

In this article, we examine some problems and biases related to the measurement of the carbon footprint for groups of households. This literature is large (e.g. Wiedmann et al. (2010); Wilting (2014); Min and Rao (2018)) but we focus on a seldom addressed question: the problem with reconstructing the distribution of the carbon footprint from spending data. To distribute the carbon footprint to subgroups (territories, cities, households...), studies often assume that the carbon footprint of a group from a particular product category is proportional to the spending of this group on that category, by lack of more appropriate data (e.g. Ala-Mantila et al. (2014, p. 133), Mach et al. (2018, p. 65)), Fremstad et al. (2018, p. 139))). Even though the limitations of this proportionality assumption are usually acknowledged in the literature (e.g. Ala-Mantila et al. (2014, p. 133)), there has been to date no discussion of this ubiquitous assumption.

In this paper, we aim to provide a systematic framework for discussing the limitations of the proportionality assumption. We purport to give researchers and statisticians analytical tools to question the robustness of their datasets and their methods, and ultimately improve both of them. Although we discuss the limitations of the proportionality assumption for the distribution of household carbon footprint, our framework can be used more broadly for any type of distribution, between other subgroups or subterritories.

We show that two channels can bias the distribution of the carbon footprint between households: the heterogeneity in prices paid and the heterogeneity in the carbon intensity of products purchased (stemming from different qual-

[1] The carbon footprint usually also includes GHG directly emitted by households, which occur mainly when they drive their combustion-powered car or heat with gas. As these GHG are not linked to a purchase but to an action (burning petrol or gas), they are generally measured directly with dedicated surveys and do not use spending, so are not subject to the biases we document. Therefore we exclude these GHG directly emitted by households from our measure of carbon footprint (in 2022 they represent 17% of the carbon footprint of France).

ities). We document that these problems arise when attempting to infer individual/group statistics when only aggregate data are available and individual/group characteristics are heterogeneous. We use case studies based on the latest French household budget survey to reveal how both channels operate, and how severe the consequences of the proportionality assumption can be on the imputed carbon footprint. For instance, the cooking oils carbon footprint appears underestimated by a third for the bottom quintile, and overestimated by two thirds for the upper quintile, with a roughly similar contribution for the price effect and the carbon intensity effect. While the general direction of the bias (under- or overestimation at the bottom or top of the income distribution) is unclear for the carbon intensity channel without more detailed data, we show that the price effect has more straightforward consequences. On average the average price paid by households increases by about .19% when equivalized income increases by 1%. As a consequence, due to the price effect, the spending method will generally tend to underestimate the carbon footprint of households at the bottom of the income distribution and overestimate it at the top of the income distribution. We finally discuss how we can advance toward getting a distribution of the carbon footprint closer to the true carbon footprint, which requires improving datasets (e.g. reporting quantities).

Our research is relevant for the carbon footprint literature. The issues discussed here can be more or less severe depending on the actual setting or the entities considered, but they are usually prevalent in most applied analyses. Although the problems are known and acknowledged (Hertwich, 2005, p. 4681), we are aware of only two works that discuss them in detail. First, Vringer and Blok (1997) have investigated, in the case of the Netherlands, how prices paid vary with income, and what are the consequences for the distribution of the carbon footprint of Dutch households. Second, Girod and De Haan (2010) compute the carbon footprint of Swiss households, with two methods (one from spending data, the other from quasi-quantity named functional units), and show that the former gives a much higher income elasticity of the carbon footprint than the latter. These two contributions are important for our discussion, yet both focus on price heterogeneity only. Our own contribution adds to these two by proposing a comprehensive framework and by pinpointing the carbon intensity heterogeneity channel. This channel is very difficult to observe but we provide a case study where it is at play.

We highlight limitations of the proportionality assumption that are conceptually not specific to the carbon footprint but can be traced back to the logic of distributing a footprint thanks to spending data. The arguments that we put forward are therefore valid more generally for the air pollutant footprint (Mach et al., 2018), the material footprint (Pothen and Tovar Reaños, 2018), the energy footprint (Baltruszewicz et al., 2023), or the water intensity of products for example (Cai et al., 2019).

The article is structured as follows. Section 2 offers a theoretical insight on the origins of problems in measuring the carbon footprint at a micro-level. We propose a framework to distinguish what we call the price effect and the carbon intensity effect. Section 3 describes the data common to our case studies.

Section 4 empirically estimates the price effect in general, and illustrates it for some selected food products. Section 5 presents a detailed case study of the carbon footprint of cooking oils, and exemplifies the price and the carbon-intensity effects as well as the data challenges to measure these effects. Section 6 discusses our results and proposes several avenues for future research.

# 2 The proportionality assumption and its problems

In a world ideally designed to compute the carbon footprint of households, three types of information would be available together : household characteristics (income, age, area of living, socio-professional category *etc*), the quantity of each good consumed by that household and the associated consumption-based (CB) emissions for each good. Despite some initiatives, the CB emissions of the products we purchase are generally not computed by the producers and thus not provided along with the rest of the products' information, such as price, origin, composition *etc.*[2].

To know the consumption of groups of households and compute their carbon footprint, researchers rely mostly on household budget surveys (HBS) that report the consumption of households on categories of goods (and in the majority of these surveys only the spending is recorded for most categories of goods). This approach, which we refer to as the "spending method", relies on the proportionality assumption: it assumes that the carbon footprint from a product category is proportional to the spending on this product category. The coefficient of proportionality can come for example from multi-regional input-output models or from life-cycle assessments, and of course depends on the product category.[3]

This proportionality assumption is widespread in the literature of carbon footprint. For example, Moran et al. (2018) computes the carbon footprint of thousands of cities, from grid data on GDP and expenditure, and "[their] model assumes that $1 of expenditure on a product category in urban vs. rural areas is equally carbon-intensive" (p.1, supplementary material). Similarly, Miehe et al. (2015) investigate carbon footprints of households at the regional level for Germany. To do so, they "assumed prices of living to be constant over all regions" (p.583), thus disregarding potential regional disparities. Dozens of studies follow this assumption (e.g. Theine et al. 2022).

The underlying rationale of the proportionality assumption is that any difference in spending reflects only a difference in the quantity of goods consumed.

[2]For the moment, there is no international obligation for companies to implement carbon accounting and to display the footprint of their products, although discussions about regulation of this kind have already started.). The association *Carbon on invoice* also pushes for a universal measure of the CB emissions for each product.

[3]For carbon intensities derived from MRIO, the resolution is constrained by the number of products available in the MRIO, and it is usually coarser because of harmonisation of product classification. For example, Ivanova and Wood (2020) use EXIOBASE, which has 200 products, and compute only 63 carbon intensities for products of the HBS.

To what extent is this assumption false? And what are its consequences?

## 2.1 An example

Let us set an example. Suppose we have surveyed spending of two households, A and B, on shirts. Household A has spent 200 € and household B 100 €. The spending of A is twice as much that of B, but what is the relationship between their carbon footprints? The answer is not straightforward and is undetermined without additional information or assumptions. The spending method assumes a proportionality between the carbon footprint and the spending on shirts.

Generally speaking, the heterogeneity of households spending may not reflect a heterogeneity in the quantity consumed of a same shirt but can come from very different channels. We identify three polar different situations:

- the quantity heterogeneity situation. Here, household B has bought the same shirts as household A, at the same price, but twice fewer in quantity. Without any doubt, the carbon footprint of household A is twice that of household B.

- the price heterogeneity situation. It can come from a pure price difference for the same good. For example, household A has bought 10 shirts at the regular price of 20 €, and household B has bought the same 10 shirts but in the sales periods, so at a discounted price of 10 €. In this case, spending differs but carbon footprints are equal. Or it can come from differences in characteristics of the product. For example, household A has bought five shirts at 40€, and household B has bought ten shirts at 10 €. The two shirts are of different quality, and probably produced with a different amount of emissions. Let us assume that the shirts bought by A and B are similar, except that the ones bought by A are embroiled with a signature of a famous basketball player, and thus command a much higher price.[4] We are not quite sure of the exact relationship, because we do not know the difference between the CB emissions of shirts bought by A and B, but we would assume that this difference is rather small. Under these hypotheses, the carbon footprint of household B would be a little less than twice that of household A.

- the carbon intensity heterogeneity situation. Irrespective of price differences, the characteristics of the products, in particular the carbon generated during the production stages, can differ. For instance, household A bought 20 shirts and household B 10 shirts, both models at 10 €. But the production processes generated twice as much GHG for the model bought by household B than for the model bought by household A. The carbon footprint would thus be the same for both households.

[4] A product with the license of a famous brand can cost more than a similar product without it, yet with a roughly similar carbon footprint. This phenomenon is already widespread and is likely to become more prevalent as intangible assets increase in the global economy.

In all these situations, the spending method would similarly estimate that the carbon footprint of household A is twice that of household B, thus producing a potentially biased picture of the relationship between the carbon footprint of the two households. To go further and investigate the size and direction of the bias, one needs to know the quantity of the goods consumed and also the exact CB emissions of the goods. One major issue for the carbon footprint literature is that this information is generally not available. The spending method introduces a gap between the imputed carbon footprint and the true carbon footprint, but the lack of information precludes any assessment of this gap.

## 2.2 Theoretical decomposition of the bias

We now propose a general framework to discuss the bias in estimating the carbon footprint from spending data. We aim at expressing the different channels discussed above that make the gap between the imputed carbon footprint and the true carbon footprint.

Let us consider a level $k$ of a classification of goods, $i$ indexes all the real-world goods that belong to $k$. Take an household $h$.[5] It consumes a quantity $q_i^h$ of good $i$ bought at price $p_i^h$.

If we knew the consumption-based emissions $f_i$ of one unit of good $i$, for each good, we would be able to compute the true carbon footprint of household $h$ for category $k$:

$$CF_{\text{true}}^{h,k} = \sum_{i \in k} f_i q_i^h \tag{1}$$

However, these data are generally not yet available as said above. The CB emissions $f_i$ for specific goods (a specific product from a specific producer) often are not known, the quantity consumed by households are not reported. Therefore, the carbon footprint of household $h$ is usually computed only from the spending of $h$ on goods of category $k$, i.e. $\sum_{i \in k} p_i^h q_i^h$, and the carbon intensity of spending on $k$ $e_k$.[6] Thus, with the spending method, the imputed carbon footprint of household $h$ for category $k$ is:

$$CF_{\text{imputed}}^{h,k} = e_k \sum_{i \in k} p_i^h q_i^h \tag{2}$$

The gap between the true and the imputed carbon footprint can be decom-

[5] The reasoning is exactly the same for a group of households (such as a quintile or decile). In that case the quantity involved is the mean quantity of the group.

[6] $e_k$ is typically estimated using either the MRIO method for an aggregate classification level $k$ or the Life Cycle Analysis method for a product $i$ and extrapolated to group $k$. These estimates are subject to uncertainties and risks of bias. Since we are interested in the distribution of the carbon footprint, we assume for simplicity that the estimate of $e_k$ is unbiased: equation (4).

posed as (see Appendix A for a derivation):

$$\frac{CF^{h,k}_{\text{true}}}{CF^{h,k}_{\text{imputed}}} = \underbrace{\left(\frac{\sum\limits_{i\in k} P_i q_i^h}{\sum\limits_{i\in k} p_i^h q_i^h}\right)}_{\text{price effect}} \underbrace{\left(1 + \sum_{i\in k}\left(\frac{f_i}{e_k P_i} - 1\right)\cdot\left(\frac{P_i q_i^h}{\sum\limits_{j\in k} P_j q_j^h} - \frac{P_i Q_i}{\sum\limits_{j\in k} P_j Q_j}\right)\right)}_{\text{carbon intensity effect}} \tag{3}$$

We have introduced $Q_i = \sum_h q_i^h$, the total quantity of good $i$ consumed by all households, and $P_i = (\sum_h p_i^h q_i^h)/Q_i$ the mean price of good $i$. We have also assumed that , for each product $k$:

$$\sum_{i\in k} f_i Q_i = e_k \sum_{i\in k} P_i Q_i\,. \tag{4}$$

Thanks to this condition, carbon intensity $e_k$ and CB emissions $f_i$ are compatible in the sense that the spending method and the exact method both provide the same aggregate footprint for each product $k$ (i.e. $\sum_h CF^{h,k}_{\text{true}} = \sum_h CF^{h,k}_{\text{imputed}}$ ).

The gap between imputed and true carbon footprints can thus be decomposed in two factors:

1. The first factor measures the bias due to the price effect: if, on average, $h$ pays higher prices to buy goods of category $k$, its imputed carbon footprint would be higher than its true carbon footprint.

2. The second factor measures the carbon intensity effect. This carbon intensity effect can arise when two conditions are satisfied:

   (a) The consumption-based emissions of different goods are not proportional to their mean prices (i.e. $f_i \neq P_i e_k$ for at least some goods $i$). This means that the proportionality assumption is violated at the level of goods. This condition is also interpreted as an existing heterogeneity in the carbon intensity of the goods (the $f_i/P_i$, which represent the emissions per monetary unit spent on good $i$ (at mean price), are not all equal).

   (b) The structure of spending of household $h$ within goods of category $k$ must be different than the average. This means that there is heterogeneity of consumption within goods of category $k$ among households.

   Both conditions should be satisfied to bias the estimation of the carbon footprint of households. The sign of the bias is indefinite. If household $h$ spends more than the average on goods that are more carbon-intensive than the average, then the imputation would underestimate its carbon footprint. On the contrary, if it spends more than the average on goods that are less carbon-intensive than the average, then the imputation overestimates it.

Therefore, in theory, neglecting differences in product carbon intensity and the unequal consumption of qualities in the population can lead to significant biases in the estimation of carbon footprint inequalities, especially if the price effect and the carbon intensity effect add up.

The rest of the article is devoted to investigate whether these two effects can be found in the distribution of the carbon footprint to households, and to what extent.

# 3 Data on consumption and carbon

To illustrate the biases introduced by these two effects on the estimation of the carbon footprint of households, we use the French HBS (*Budget de famille*, shortened in BdF) in its latest available version (2017).[7] This Insee (French national statistics institute) survey collects information from households from two different processes: an interview and a logbook. The surveyed households fill the logbook during one week, with all transactions done.

The logbook contains many pieces of information that we analyse to reveal the heterogeneity of the prices paid, and the quantities consumed, by all the surveyed households $h$, for a given category of product $k$. The monetary amounts of the purchase (i.e. expenditures, $p_k^h q_k^h$) is registered, but for most goods, the quantity purchased ($q_k^h$) is also available. From information about expenditures and quantities, we can also reconstruct the price per unit of good ($p_k^h$).

Table 1 describes the data cleaning steps. The quantity is almost always observed in the logbook dataset, but rarely in the interview dataset. The table displays the number of observations for which we have reliable information about prices and quantities. We have this information for 797 products (out of 921 in the raw data) and 16 140 surveyed households (out of 16 977), representing 28.4 million households (out of 29.4 million). These products represent 27.5% of total expenditures.

Table 1: Data processing

| | # Observations | Share of spending | Share of transactions |
|---|---|---|---|
| Raw data | 1376599 | 100.0 | 100.0 |
| Without missing spending | 1376576 | 100.0 | 100.0 |
| Without missing quantity | 679991 | 35.1 | 49.9 |
| With only most representative unit | 481483 | 29.4 | 35.3 |
| Scope of household final consumption | 479669 | 27.4 | 35.1 |
| At the household level | 300839 | 27.4 | 35.1 |
| Without negative spending | 300489 | 27.5 | 35.1 |

**Notes:** The number of observations provides the number of lines in the dataset considered. The share of spending gives the weighted share of spending that remains after different data processing steps, compared to the raw data. The share of transactions provides the weighted share of transactions made by households that remain after these data processing steps, compared to the raw data. The line *With only most representative unit* selects only the transactions for which the unit is the same as the most commonly used for that product. The line *Scope of household final consumption* omits products from the category 13 of the COICOP nomenclature, which includes taxes, credit payments, gifts. The line *Without negative spending* excludes the discounts, which cannot be easily linked to specific products.
**Sources:** BdF 2017.

Additional data are used in Section 4 and Section 5. The Agribalyse database

[7] https://www.insee.fr/en/metadonnees/source/operation/s1341

version 3.1, provided by Ademe (French energy transition agency,[8]) provides the CB emissions per unit of goods in another nomenclature. For a subset of consumption goods items, we find a match with the categories available in the HBS database. For this level of nomenclature (the finest available in the HBS), we thus know quantities, prices (from HBS) and CB emissions (from Agribalyse). We use this information in Section 4 and Section 5 to compute the true carbon footprint, according to equation 1.

In Section 5, we also use the Nielsen database. Nielsen is a company that crosses cash register data (from supermarkets and hypermarkets for example) with consumer panel data in order to obtain the most representative vision possible of French household consumption. Insee uses these data to complete its other sources on household consumption expenditures. We combine the Nielsen dataset with BdF to obtain price and total quantity consumed by French households ($Q_i$) for each variety of oil $i$ for which we know the CB emissions from Agribalyse. The procedure followed is explained in Appendix D.

# 4 Estimation of the price effect

In this section, we focus on the first factor of difference between the imputed carbon footprint and the true carbon footprint: the price effect. The price effect depends on how prices paid by households deviate from the average. We empirically study how prices vary across households grouped by equivalized disposable income.[9] We provide evidence of price heterogeneity by income groups and compute the price elasticity of income for each category of goods. Finally, we compute the true and imputed carbon footprints of some products for each income group and show how the price effect biases the distribution of carbon footprint.

## 4.1 Price heterogeneity among households

The higher the equivalized income, the higher the prices that the households pay for the goods they buy. Figure 1 shows the distribution of all the prices paid in each ventile[10] of equivalized income on the 797 products of our dataset. 25% of the prices are above 6,43 € in the bottom ventile of the distribution, versus 11,80 € in the top ventile.[11]

To provide an idea of the difference in prices at both ends of the income distribution, we compare the prices paid by households in the top and the bottom

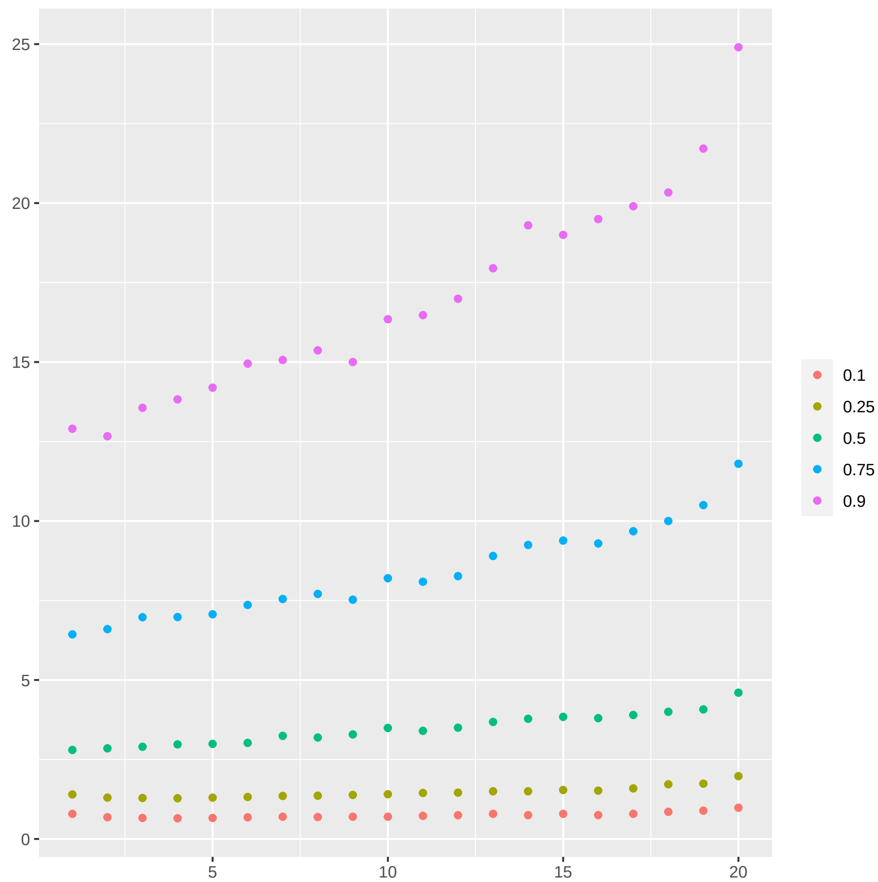
[8] https://agribalyse.ademe.fr/

[9] This is disposable income divided by consumption units (based on number and ages of members of the household), also called standard of living. We use equivalized income or income for short).

[10] That is a twentieth of the population ordered by increasing equivalized income.

[11] Not all products are bought by each category of households. But taking out the difference in the composition of the set of products between different categories of households leaves the results virtually unchanged. Figure B.1 reproduces Figure 1 when we restrict to the products that are bought by at least one household in each ventile.

Figure 1: Distribution of the prices by ventile of equivalized income




**Notes:** This Figure plots the percentiles 10, 25, 50, 75 and 90 of the distribution of prices for each ventile of equivalized income, in euros. 300 488 observations on 797 products.

**Sources:** BdF 2017 ; authors' calculation.

5% for the same products. Among the 541 products that at least one household in each of these two ventiles buys, a household in the top ventile pays on average a price twice higher than a household in the bottom ventile. Four products out of five are paid at a higher price in the top 5%, and almost a quarter of the products are paid in the top at prices more than double than those in the bottom ventile.

The elasticity of the price of goods with respect to equivalized income summarizes how heterogeneous these prices are. For a given product $i$, this elasticity, measured by the parameter $a_i$ in regression (5), captures the percentage increase in the price paid for good $i$ that is observed when equivalized income increases by 1%. We exclude here households with negative equivalized income, and products bought by fewer than 100 households (375 products left).

$$\log(Price_{h,i}) = a_i \log(Income_h) + c_i + \varepsilon_{h,i} \quad (5)$$

Our results suggest that the prices of purchased goods increase markedly with household income. Figure 2 represents the 375 elasticities $a_i$ in correspondence with the number of households buying the product. The elasticities are positive and fluctuate around the average of 0.19: on average, when equivalized income increases by 1%, the price of the goods bought increase by .19%. The price of the entire average consumption basket would increase by .18% (the average elasticity weighted with spending[12]). The products with more transactions tend to be food products and to have slightly lower elasticities.

This is not far from the results obtained by Vringer and Blok (1997) from the 1995 budget survey of Dutch households. They found that food consumption categories have generally a low elasticity of prices, lower than what we find. They estimate the average elasticity of prices to be 0.11 (unweighted) and 0.16 (weighted).

All in all, prices differentials appear pervasive and large between households with different equivalized incomes. Richer households pay higher prices : a 1% increase in equivalized income increases the average price paid by about .19%. As a consequence, the spending method, which does not correct for the price heterogeneity, will generally tend to underestimate the carbon footprint of households at the bottom of the income distribution and overestimate it at the top of the income distribution. The price effect could also bias the carbon footprint of other social groups as soon as the price they paid is systematically different from the average.

## 4.2 Bias in the carbon footprint of single products

We compute on a selection of products how this heterogeneity in prices along the income distribution translates into differences in the carbon footprint of (categories of) households.

[12] The elasticities that are not significantly different from zero at the 5% confident level could be set to zero to be conservative. The figure would drop only to 0.16.

Figure 2: Elasticity of the price with respect to equivalized income


**Notes:** The points represent the coefficients $a_i$ from the regression (5). The x-axis shows the number of surveyed households buying product $i$. Only the 375 products with at least 100 surveyed households buying them are shown. The horizontal line shows the sample simple average of .19. The simple average elasticity in each broad category is shown in parenthesis.

**Sources:** BdF 2017; authors' calculation.

To do so, we consider the level of nomenclature $k$ to be that of a specific product (like rice) for which HBS provides expenditures and quantities, and thus prices. We assume that there is no further heterogeneity, that is all different varieties (basmati rice, arborio rice, jasmine rice,...) have the same carbon intensity. Under this assumption, there is no carbon intensity effect.

Under the assumptions of no heterogeneity within product $k$, equation (1) amounts to $CF^{h,k}_{\text{true}} = f_k q^h_k$ and equation (2) to $CF^{h,k}_{\text{imputed}} = e_k p^h_k q^h_k$ (with $e_k = f_k/P_k$ from the compatibility condition (4)). The gap between the 'true' and the imputed carbon footprints is thus only due to the price heterogeneity among households and reduces to the price effect:

$$\frac{CF^{h,k}_{\text{true}}}{CF^{h,k}_{\text{imputed}}} = \frac{P_k}{p^h_k} \tag{6}$$

We use the database Agribalyse to get the CB emissions $f_k$ (see section 3). We select some HBS products which meet a set of conditions: first, they must be consumed by each ventile of the income distribution frequently enough so that the results are not driven by outliers; second, it is possible to match them with products from the Agribalyse dataset that have similar CB emissions;[13] third, they belong to the food and beverages category, for which quantities are particularly comparable between households. Rice, fruits' juice and wine meet these criteria.[14] Table 6 in appendix provides the CB emissions of the Agribalyse's goods matched with these three products.

Figure 4(a) provides the true carbon footprint of the rice purchased by households in each category (as described in equation 1 but for only one product, with the blue bar), and the imputed carbon footprint (equation 2, with the yellow dot). The carbon embedded in the annual rice consumption stands at 23.8 kg $CO_2$ for the average household, but 55.6 kg $CO_2$ for an average household in the

[13]The Agribalyse dataset provides information at a finer level than the French HBS. We focus on the products reported in the HBS that can be matched with Agribalyse's goods that are relatively homogeneous in their CB emissions, so that our assumption of no within-heterogeneity is empirically grounded. Even if different groups of households consume different goods to which a product is mapped, the low deviation in their CB emissions means that the average CB emissions provide an accurate CB emissions for the product. The CB emissions of a HBS product is computed as the simple average of the CB emissions of the corresponding Agribalyse goods.

[14]Rice is purchased by 2183 surveyed households with a positive quantity and in the most frequently used unit, representing 2.7 million households. The corresponding figures for wine are 2361 (4.8 million) and for juices 5006 (8.0 million). Each of these 3 products is purchased by at least 66 surveyed households in every ventile. As Table 6 shows, the CB emissions are similar among the Agribalyse wine products or among the rice products. For the products in the fruit juices category, which is much more detailed, the CB emissions are also comparable to each other, bar the two pineapple juices, which have higher CB emissions. Despite the low share of pineapple fruit juice in fruit juice consumption, at 4 % in 2021 in France according to Unijus citing Nielsen data in CAM P1321, their higher CB emissions could still impact our results, given our focus on detailed income categories. For the fruit juice, the quantitative validity of the price effect that we identify thus relies on a roughly similar consumption of pineapple fruit juice by income category. While this assumption appears reasonable, we did not find evidence related to the link between income and pineapple juice consumption in the literature.

lowest ventile. The price effect bias is thus visible with the difference between the blue bar and the yellow dot. The spending method underestimates the emissions linked to the consumption of rice for the bottom ventiles of households, by up to a quarter for the $1^{st}$ ventile, which accounts for 12.2% of emissions associated with rice with the true carbon footprint method, versus 9.3% with the imputed one. It overestimates slightly emissions by households in the top ventiles, while the estimations for the middle of the distribution do not appear to be much affected. The carbon footprint associated with juices and wine appears underestimated for the households below the median equivalized income, and overestimated for the other half of households (Figures 4(b) and 4(c)). As can be seen from the figure, the bias can be substantial: for juices or wine, the imputed carbon footprint turns out to be overestimated by half in the top ventile.

Extending this analysis to the entire consumption basket would require the CB emissions for each item purchased by households, that we do not have in our dataset. In Appendix C, we propose a very rough estimate of the price effect on the whole consumption basket using aggregated data from the national accounts and the national carbon footprint by product: the price effect would lead to a carbon footprint overestimated in the top decile and underestimated in the bottom decile, by more than 10% in both cases. Vringer and Blok (1997) attempted to compute the consequences of the price heterogeneity on the distribution of energy requirements (or, in modern parlance, energy footprint). Assuming that the price heterogeneity where it cannot be observed is the same as where it can be observed, they found that correcting for it lowers the income elasticity of energy requirements from 0.63 to 0.6-0.56 depending on the assumptions. However, to get their results, they assume that there is no further carbon intensity heterogeneity. We delve into additional source of this heterogeneity in the next section.

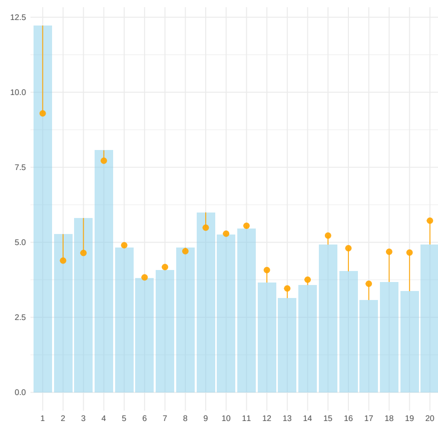
# 5 The case of cooking oils, with combined price and carbon intensity effects

This section investigates the interplay of the price effect and the carbon intensity effect (see section 2). To illustrate how this can bias the distribution of the carbon footprint, we take as an example the case of cooking oils. Cooking oils are a good case study because they are consumed at all income levels and face a double heterogeneity: different types of oils have both different prices and different carbon intensities.

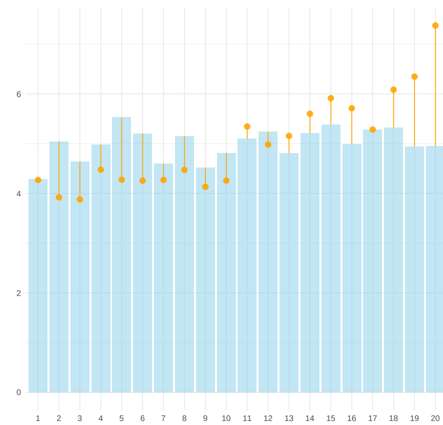
The French HBS (BdF 2017) provides quantities and prices for each household for only two categories of cooking oils ("olive oil" and "other oils"). Both categories are consumed by households at all levels of income.[15] According to

[15] 1865 surveyed households, representing 2.5 million households, buy the "other oils" product in BdF 2017. There are at least 52 households in each ventile of equivalized income. Olive oil is less frequently consumed, with 768 surveyed households, representing 1.5 million households, and at least 26 households in each ventile.

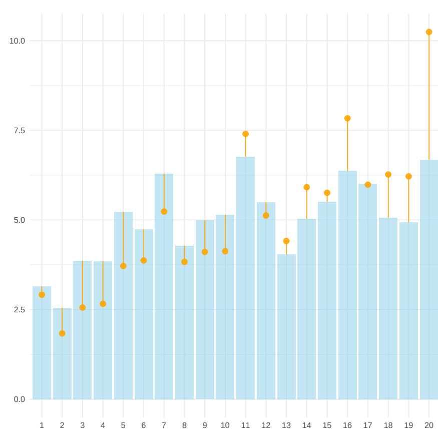
Figure 3: Mismeasurement of the carbon footprint due to the price effect




(a) Rice




(b) Fruit juice




(c) Wine

**Notes:** The blue bars show the true annual carbon footprint for 3 products of each ventile of households, as a share of the total (in %). They are computed as the weighted sum of the true carbon footprint among households in each ventile, divided by the total. The weights used are the household weight. The yellow dot shows the imputed carbon footprint of each ventile, as a share of the total (in %). The number of observations used, i.e. the number of surveyed households purchasing this product, with a positive quantity and in the unit most often used, is 2183 for rice (unit kg), 5006 for fruit juice (unit kg) and 2361 for wine (unit L).

**Sources:** BdF 2017, Agribalyse 3.1.

the Agribalyse dataset, if "olive oil" can be associated with a single number of CB emissions, there are many types of other oils, with different CB emissions. The "other oils" category exhibits within heterogeneity and thus cannot be assigned CB emissions in a straightforward manner.

To investigate further the "other oils" category, we need data about the aggregate consumption and CB emissions of each of these oils. We match the Agribalyse dataset with the Nielsen dataset to find nine other oils for which we have both data. The Nielsen database provides the total consumption and average price at the country level for each of these nine oils and we integrate[16] it with BdF 2017 to obtain a disaggregation of the "other oils" category, consistent both in prices and in quantities. This allows us to compute for each household group the average CB emissions of the "other oils" category, as well as the carbon intensity.[17] All the information is reported in Table 2.

The different oils are heterogeneous both in terms of relative prices, with a range of 1 to 9.1, in terms of CB emissions ($kgCO_2$ / kg of product), which range from 1 to 8.2, and in terms of carbon intensity ($kgCO_2$ / €) with a range of 1 to 13.5 from olive oil (the least carbon-intensive) to rapeseed oil (the most carbon-intensive). The total quantities consumed are also varied, ranging from an average of 2000 liters per year for soybean oil to 112 million liters for sunflower oil. For example, hazelnut oil is 4 times more carbon-intensive than olive oil (and emits 8 times more by kg), costs twice as much, but is about 300 times less consumed.

Table 2: Aggregate data on oils

| Product category | Aggregate consumption (thousands of L) | Mean prices (euros 2017 / L) | CB emissions (kg $CO_2$ / kg) | carbon intensity ($kgCO_2$ / €) |
|---|---|---|---|---|
| Olive oil | **86 075** | **7.88** | **1.00** | **0.117** |
| Hazelnut oil | 272 | 17.06 | 8.20 | 0.442 |
| Peanut oil | 4 595 | 3.72 | 4.26 | 1.054 |
| Rapeseed oil | 27 792 | 1.88 | 3.24 | 1.582 |
| Sesame oil | 223 | 15.97 | 3.24 | 0.186 |
| Combined oil | 32 265 | 3.10 | 3.02 | 0.895 |
| Various frying | 21 880 | 2.16 | 2.71 | 1.155 |
| Soy oil | 2 | 9.44 | 2.65 | 0.259 |
| Sunflower oil | 112 007 | 1.88 | 2.58 | 1.265 |
| Grapeseed oil | 3 361 | 4.99 | 1.29 | 0.238 |
| "other oils" | **202 397** | **2.23** | **2.78** | **1.145** |
| All types of oils | **288 472** | **3.92** | **2.25** | **0.528** |

Note : Combined oils means multiple mixed cooking oils.

**Sources:** Agribalyse 3.1, Nielsen 2017, BdF 2017; authors' calculation.

According to the theoretical analysis of subsection 2.2, we need heterogeneity in both the carbon intensity and the consumption structure to observe the

[16]More information on matching and integrating the datasets is available in Appendix D.

[17]CB emissions are given in $kgCO_2$/kg of product and prices in €/ L, so we need the density to compute the carbon intensity (in $kgCO_2$/€). We assume an equal density of 0.92 kg/L for all oils. In reality, the densities of vegetable oils can range between 0.91 and 0.93 (https://www.aceitedelasvaldesas.com/en/faq/varios/densidad-del-aceite/), but this does not significantly affect our results.

carbon intensity effect. The case of cooking oils meets the first condition. Regarding the second, we lack the information detailing the quantities consumed within the "other oils" category. We therefore take a two-step approach. In subsection 5.1, we only make use of the consumption data available in HBS and thus focus on the difference between "olive oil" and "other oils", ignoring the heterogeneity within the "other oils" category. Investigating the consequences of this heterogeneity is postponed to subsection 5.2. There, we estimate different possibilities for the distribution of purchases within "other oils" category by income quintiles,[18] possibilities that are both compatible with HBS and Nielsen data. In both subsections, we describe how the – estimated – true carbon footprint varies by income groups and compare it to the carbon footprint imputed with the spending method. We break down the bias of the latter into the price effect and the carbon intensity effect.

## 5.1 Carbon footprint from oil consumption with partial heterogeneity

We assume for the time being that the "other oils" category is a homogeneous product whose CB emissions are 2.78 kg $CO_2$/kg (calculated as a weighted average, see Table 2). Because of the substantial heterogeneity of carbon intensity within this category, this amounts to assuming that all households consume all types of "other oils" in the same proportion.

In the HBS data, the consumption structure between "olive oil" and "other oils" varies among income groups: the second condition for the carbon intensity effect is thus valid for the product cooking oils. Figure 4 represents the share of each quintile of equivalized income for the overall consumed quantities and spending for the two categories: "olive oil" and "other oils".

First, when examining the difference between quantities and spending within these two categories, we have again evidence that the paid price increases with income : the share of spending is higher than the share of quantities for high income quintiles, and lower for low income quintiles.[19]

Second, consumption of these two categories evolves differently with income. In the case of "olive oil", the quantities and spending both increase with income. In the case of "other oils", the quantities decrease with income while the spending is roughly flat and then increases at the top. This shows that the consumption structure is heterogeneous: the upper quintiles consume relatively more olive oil, the lower quintiles relatively more other oils.

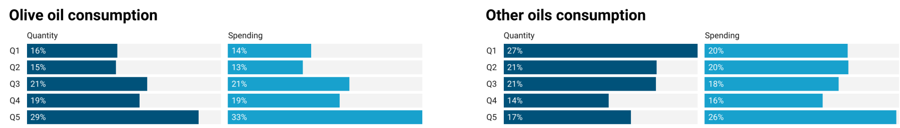
For these data on cooking oils, consumption structure and carbon intensity interact in a specific way: consumption at the top of the income distribution

[18] In this section, we use a decomposition of only five income groups because the consumption data for each type of oil is less precise and quintile decomposition is sufficient enough for our arguments.

[19] The price difference is highly noticeable for the "other oils" category and greater than for "olive oil". This may be the consequence of the underlying price heterogeneity within the "other oils" category (i.e. that high income households buy types of oils that are more expensive, and not that they buy the same oils at higher prices), see next subsection for a discussion.

is preferably directed to the least carbon-intensive oil ("olive oil"), whereas consumption at the bottom of the income distribution is preferably directed to the most carbon-intensive oil ("other oils"). Therefore, independently of any price effect, distributing the carbon footprint proportionally to spending will, in this case, overestimate the carbon footprint at the top and underestimate it at the bottom.

Figure 4: Shares of oil consumption by equivalized income quintile




a. Olive oil    b. Other oils

**Notes**: This figure provides the share of each quintile of households among all households for the quantity (in blue) and the spending (in orange), for "olive oil" (left panel) and "other oils" (right panel).

**Sources:** BdF 2017

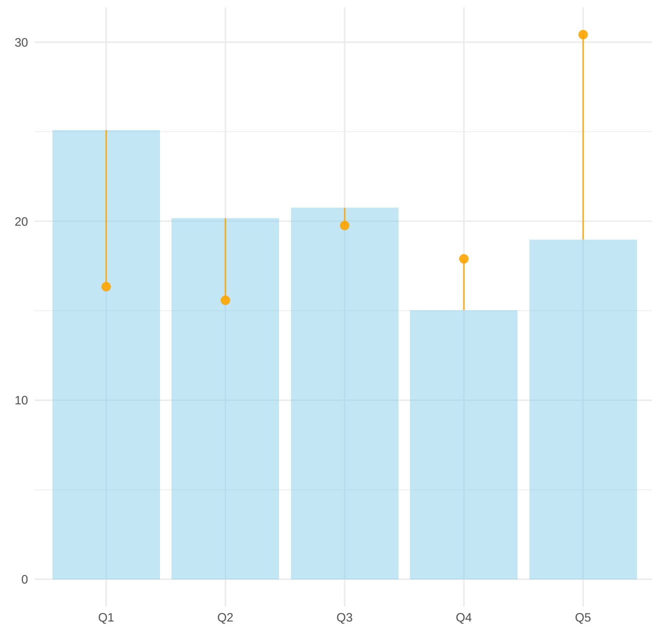
In Figure 5, we compute the share of the aggregate carbon footprint of cooking oils of each income quintile, according to the two methods, by distributing the carbon footprint in line with spending (the (imputed) spending method) or with the consumed quantities (the (estimated) true method). The quantity method multiplies the observed oil quantity consumed by the CB emissions for the two types of oil. The spending method, whose accuracy relies on the proportionality assumption, allocates the average carbon footprint proportionally to the spending for all oils ("olive oil" plus "other oils"). It does not leverage the distinct price and carbon intensity for these two categories and distributes the footprint on the basis of the average carbon intensity ($e_{oils} = 0.53$ kg $CO_2$/€).[20]

Under the (too strong, see below) assumption of no heterogeneity within the "other oils" category, the quantity method gives an estimation of the true carbon footprint. The spending method deviates from the quantity method due to both the price effect and the carbon intensity effect. The results are as expected given the carbon intensities and the consumption profile we have found in the data: the spending method overestimates carbon footprint at the top and underestimates it at the bottom. In numbers, the differences are telling. The ratio between the carbon footprint of the top quintile and of the bottom quintile (ratio T20/B20) is 0.76 according to the quantity method (1.91 for olive oils and 0.65 for other oils), versus 1.86 according to the spending method (2.34

[20]For illustrative purposes, we also computed the carbon footprint according to a third intermediate disaggregated spending method: the carbon footprint of each of these two categories is distributed proportionally to the spending of each category, and then added to obtain the carbon footprint from oil consumption. In this disaggregated spending method, we use distinct carbon intensities for "olive oil" and "other oils". The disaggregated spending method takes into account the difference in carbon intensities between "olive oil" and "other oils", but does not correct for the price effect. The carbon footprint profile for this method is intermediate between the profiles of the quantity method and the spending method (see appendix E.1 for more details on this method).

for olive oils and 1.34 for other oils). According to the spending method, the 20% wealthiest are responsible for 30.4% of the carbon footprint of oil consumption, but only 18.9% according to the quantity method.

Figure 5: True and imputed carbon footprint of oil




**Notes:** The blue bars represent the true carbon footprint of each quintile of households, as a share of the total (%). The yellow dots show the imputed carbon footprint, as a share of the total (%).

**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017; authors' calculation

The gap between the true carbon footprint (estimated with the quantity method) and the carbon footprint imputed with the spending method can be decomposed into the price effect and the carbon intensity effect.[21] In our specific example of oils, both are sizable and introduce biases in the same direction: an underestimation of the carbon footprint by 18% at the bottom quintile for each factor, and an overestimation of 24% (price effect) and 34% (carbon intensity effect) for the top quintile (Table 3). All in all the oil carbon footprint appears underestimated by a third for the bottom quintile, and overestimated by two thirds for the upper quintile, with a roughly similar contribution for the price effect and the carbon intensity effect.

The case of cooking oils is striking because the very direction of the correlation between income and carbon footprint is reversed depending on the method.

[21] See (3) for the general formula, or appendix E.1 for a specification of the formula in this case.

The imputed carbon footprint based on spending increases from bottom to top quintile whereas the carbon footprint estimated from quantities actually decreases from bottom to top quintile. The bias of the spending method is particularly strong in this case because price and carbon intensity effects play in the same direction. This case also shows that it is important to take into account both effects to arrive at the actual profile. Indeed, correcting the spending method for only one of the effects is not sufficient to recover the actual decreasing profile of carbon footprint (i.e. ratio T20/B20 is 1.86 according to the spending, 1.24 when correcting for the price effect alone, 1.14 when correcting for the carbon intensity effect alone. None of these ratios are below 1, contrary to the ratio obtained with the quantities and estimated at 0.76).

Table 3: Gap between the true and the imputed carbon footprint (with homogeneity within the "other oils" category), broken down into the price effect and the carbon intensity effect

| | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| $CF_{\text{imputed}}/CF_{\text{true}}$ | 0.65 | 0.77 | 0.95 | 1.19 | 1.60 |
| price effect | 0.82 | 0.89 | 0.96 | 1.03 | 1.24 |
| carbon intensity effect | 0.79 | 0.87 | 1.00 | 1.15 | 1.30 |

**Notes:** This table provides the ratio of the imputed carbon footprint over the true carbon footprint, under the assumption of homogeneity within the "other oils" category, by income quintile and for cooking oil. The inverse of the factors (price effect and carbon intensity effect) described in (3) are shown (also see Appendix E.1 for a specification of the formula in this case).

**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017 ; authors' calculation

## 5.2 Carbon footprint from oil consumption with full heterogeneity

We now delve into the heterogeneity of the "other oils" category, that was assumed away in the previous subsection. This has two aims: first, to evaluate the robustness of the results previously found; second, to further highlight the problematic consequences of the heterogeneity in carbon intensity of goods for the distribution of the carbon footprint.

The results obtained so far rely on the assumption that the different oils from the "other oils" category are consumed in the same proportion by the different groups of households, an assumption we had to make because we do not know what kind of "other oils" are actually consumed by each household. It is therefore conceptually possible that the results are not robust to alternative assumptions. At first sight though, the results seem to be driven mainly by the difference between olive oil and sunflower oil, which represent two thirds of the quantities consumed. We are therefore quite confident that our previous results are robust but can test them further.

To estimate the true carbon footprint with full heterogeneity, we need more assumptions about how "other oils" consumption is distributed by income groups. The "other oils" category comprises nine kinds of oils, whose aggregate consumed quantities are given by Nielsen data (see Table 2). Our main idea for this robustness check is to distribute the quantities of these nine types of oils between household groups, while preserving the aggregate consumption of each type of oils and the total consumption of each household group. Because we are interested by the whole possible range of the true carbon footprint, we first investigate two polar cases that attribute the quantities of the most emitting (in terms of CB emissions) "other oils" to the two ends of the distribution, either to the richest or to the poorest. In addition to these two polar cases, we also randomly distribute the quantities consumed while respecting the set of constraints (aggregate and household groups observed consumption), and we repeat that operation 1000 times.[22]

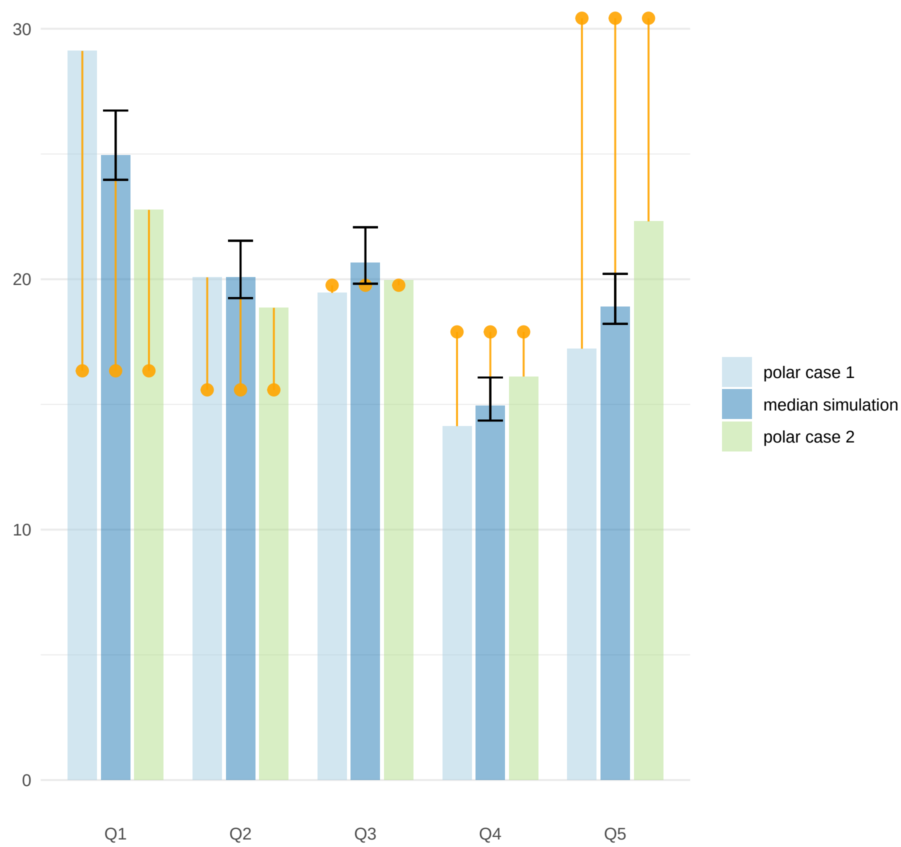
The various resulting estimations of the true carbon footprint of all oils are reported in figure 6, as well as the carbon footprint imputed by the spending method in yellow dots (already shown in figure 5). The median and the 2.5% and 97.5% percentiles of the distribution of the carbon footprint of each household group obtained from the 1000 simulations are also reported. Unsurprisingly the carbon footprint of the bottom quintile is at the highest according to the polar case allocating the most emitting "other oils" to the poorest, whereas the carbon footprint of the top quintile is at the highest according to the other polar case (allocating the most emitting "other oils" to the richest). The simulated distributions are intermediate compared to the two polar cases and the median case is similar to the carbon footprint profile estimated by quantities in figure 5.

These results show how the heterogeneity in CB emissions of products is important and fundamental to be taken into account to precisely compute the distribution of the carbon footprint. Indeed, depending on the polar case, the ratio T20/B20 can be estimated at 0.49 or 0.89. The assumption chosen to tackle missing information thus makes a difference for the estimation of the true carbon footprint by income group.

However, it is equally important to notice that in this case study the uncertainty in our reconstruction of the true carbon footprint is far smaller than the gap between the true carbon footprint and the imputed carbon footprint (see also Table 8 above). Indeed, the ratio T20/B20 is at most 0.89, under the extreme scenario where the most emitting oils are bought by the wealthiest, whereas the same ratio was estimated at 1.86 according to the spending method. This means that the reversal of the correlation between income and carbon footprint obtained in the previous subsection is actually robust for our case of cooking oils: whereas the spending method would indicate that the carbon footprint increases with income, the true carbon footprint from oil consumption could decrease with income and is at most flat with income (T20/B20 close to 1 but not above).

[22] See Appendix D.3 for details.

Figure 6: Different estimations of the true carbon footprint of oil consumption, and carbon footprint imputed with the spending method, by equivalized income quintiles




**Notes:** This figure provides the share (in %) of each quintile in the total carbon footprint of all types of oils following different methods. The yellow dots show the carbon footprint imputed with the spending method. The median and the 5% interval from 1000 simulations of the true carbon footprint is shown. Polar case 1 (2) corresponds to the attribution of the most carbon-intensive oils to the lowest (respectively highest) income households.
**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017 ; authors' calculation

These results confirm that the spending method tends to overestimate the carbon footprint at the top of the income distribution and underestimate it at the bottom. In our example of cooking oils, it even reverses the correlation between income and carbon footprint. The price effect introduces naturally a bias in this direction and for the case of oils, the carbon intensity effect plays in the same direction. As we have said, the main driving force is the interplay between a carbon intensity of olive oil lower than that of sunflower oil, and a greater consumption of olive oil at the top of the income distribution. However, for the case of oils, the pattern observed for these two oils is more general. It is indeed striking to observe in Table 2 that the most expensive oils (hazelnut oil and sesame oil) have also a carbon intensity below the average. Even if we have no detailed information on which households consume these oils, their prices suggest that they would be consumed more by wealthy households, which can be backed by casual knowledge of consumption habits in France. The carbon intensity of the spending of wealthy households would thus be below the average. So if the specificity of olive oil explains the size and direction of the carbon intensity effect, considering other oils that are more likely to be consumed at the top of the income distribution gives the same message here: the carbon intensity of spending more likely to be done by wealthy households is below the average, which means the spending method would also overestimate their carbon footprint.

We further decompose the price and carbon intensity effects for the two polar cases, in Table 4 and Table 5.[23] The carbon intensity effect evolves around the "reference" effect found in Table 3. As expected, for the bottom quintile, it is below the "reference" effect for polar case 1 (that attributes the most emitting oils to the bottom quintile), and above the reference effect for polar case 2. This indicates that the spending method underestimates the true carbon footprint more in polar case 1 than in polar case 2 because of the carbon intensity effect. Furthermore, in both cases, the spending method underestimates the true carbon footprint because of the carbon intensity effect (carbon intensity effect below 1), and this is driven by the difference between "olive oil" and "other oils" investigated in previous subsection. For the top quintile, the situation is analogous, but of course reversed between polar case 1 and polar case 2.

The price effect exhibits less variation around the "reference" effect of Table 3. One can notice that the price effect for bottom quintile is well below 1 in polar case 1, far more than the "reference" effect. This means that the bottom quintile pay its oils at much cheaper prices than the average. The price effect in polar case 1 is particularly strong because we have allocated some expensive oils to the bottom quintile. However, rapseed oil, which is both carbon-intensive and cheap, is also allocated to the bottom quintile in polar case 1, which mitigates the effect. The rapseed oil explains why the price effect for top quintile is not reduced more strongly in polar case 2 (allocating the most expensive oils to the top quintile would tend to cancel out the price effect).

To get a better sense of the plausibility of the polar cases, we can look more closely at the relationship between actual expenditures, quantities allocated in polar cases and mean prices. We can infer the price paid by the quintile for the

[23] Not surprisingly, the median case decomposition is very close to the decomposition with two oils categories of Table 3. In fact, as Table 8 in Appendix E.2 shows, a random allocation of the different kinds of "other oils" is highly unlikely to yield a true measure that would be close to the imputed carbon footprint of the spending method, for any of the five quintiles. Furthermore, the price and the carbon intensity effects are also all unlikely to be close to 1, except for the intensity effect in the third quintile or the price effect in the fourth quintile.

oil that is also consumed by other quintiles (in both case, it is combined oil, see Appendix D.3). In polar case 1, bottom quintile pays too low a price, implying that too expensive oils have been allocated in full to this quintile (i.e. hazelnut oil and sesame oil). In polar case 2, top quintile pays too high a price, implying that too cheap oils have been allocated in full to this quintile (i.e. rapeseed oil). While being possible, both polar cases are financially implausible. This confirms that the polar cases are extreme situations that strictly bound the possible range of the true carbon footprint.

Table 4: Decomposition of the gap between the true and the imputed oil carbon footprint into the price and the carbon intensity effects - polar case 1

| | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| $CF_{\text{imputed}}/CF_{\text{true}}$ | 0.56 | 0.78 | 1.02 | 1.27 | 1.77 |
| price effect | 0.75 | 0.87 | 1.02 | 1.09 | 1.25 |
| carbon intensity effect | 0.75 | 0.89 | 1.00 | 1.16 | 1.42 |

**Notes:** The polar case 1 corresponds to the allocation of the most carbon-intensive oils to the richest households. See notes of Table 3.

**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017 ; authors' calculation

Table 5: Decomposition of the gap between the true and the imputed oil carbon footprint into the price and the carbon intensity effects - polar case 2

| | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| $CF_{\text{imputed}}/CF_{\text{true}}$ | 0.72 | 0.83 | 0.99 | 1.11 | 1.36 |
| price effect | 0.85 | 0.96 | 0.99 | 0.91 | 1.21 |
| carbon intensity effect | 0.84 | 0.86 | 1.00 | 1.21 | 1.13 |

**Notes:** The polar case 2 corresponds to the allocation of the most carbon-intensive oils to the poorest households. See notes of Table 3.

**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017 ; authors' calculation

The exercise we have done for quintiles could be replicated by decile or even percentile, if more accurate data on oils were available. However, the finer the granularity of income groups is, the more uncertain the "true" carbon footprint becomes. The assumption to distribute the quantities has a greater impact on the carbon footprint of small groups than on that of large groups. To take an example, the carbon footprint of the top 10%, top 1%, or even worse, the top 0.1% could vary considerably if the specific consumption of hazelnut and peanut oil is attributed to these groups, and can become much higher than the one which assumes a homogeneous product. This issue arises when specific products have CB emissions that are significantly higher than the average but are consumed in small quantities, which then leads to a higher carbon footprint of the income groups they are attributed to. The smaller the income group, the higher the spread.[24] Using surveys would complicate further any analysis for very detailed groups, but that issue would already arise with exhaustive data.

The biases we have demonstrated in the previous two subsections are not unique to oils and could be more severe for other consumption goods, such as air travel or meat, for which the carbon content is on average high and can vary a lot among varieties. In the case of meat, the bias is likely to be more pronounced since the CB emissions of meat varies widely, ranging from 12 to 99 $kgCO_2/kg$ between poultry and beef (Poore and Nemecek (2018)).

# 6 Discussion and conclusion

In this article, we examined the common practice of reconstructing the distribution of the carbon footprint from spending data, using a proportionality assumption between CB emissions and expenditures. We provided a systematic framework for discussing the limitations of this usual practice of the literature. Using a few selected food products in France, we found that this assumption leads to significant biases in the distribution of the carbon footprint from these products.

While the theoretical framework can be used for a general discussion, our empirical analysis is limited to some items and to the French context. Nevertheless, various considerations suggest that the bias would be significant for total consumption patterns, as well as in most national contexts. In accordance with the literature, we observe that prices paid increase with income for a whole range of products, a feature that likely holds in most situations. This should translate into a price effect that overestimates the carbon footprint at the top of the distribution and underestimates it at the bottom. A tentative estimate of its magnitude on the whole consumption basket points to an underestimation of the carbon footprint in the bottom decile, and an overestimation in the top decile, by more than 10% in both cases. There is much less evidence about systematic biases in the distribution due to the carbon intensity effect (which depend on the granularity of the data). The carbon intensity effect could be higher for some products than for our example of cooking oils, with a higher heterogeneity in carbon intensity of products (e.g. meat). But it is not clear whether the most carbon-intensive goods may be consumed systematically more or less at the top of the income distribution, thus leading to underestimation or overestimation of the carbon footprint of the top income. Additional work and more detailed data

[24] To give a toy example, consider a population which consumes a product that exists in two versions, one that emits 1 and one that emits 11. On the aggregate, for 99 units of the low-emitting version, only 1 unit of the high-emitting version is consumed. Each household consumes the same quantity $q$, but we do not know which version. What would be the carbon footprint? Assuming the product is homogeneous, for instance because of the availability of the CB emissions at the aggregate level only, gives a carbon footprint of $1.1q$ for every household. Depending on which groups consume the high-emitting version, the average of a quintile average varies from $q$ to $1.5q$, the average of a decile varies from $q$ to $2q$, and the average of a percentile varies from $q$ to $11q$. Note however that, in this example, from groups smaller than the percentile, the average carbon footprint still varies from $q$ to $11q$.

are needed before we can formulate general statements. We have chosen cooking oils due to the availability of their CB emissions and it happens to be a case where the wealthiest consume the least carbon-intensive goods. This indicates that the situation where the carbon footprint of top income is overestimated because of the carbon intensity effect may not be uncommon.

Overall, the proportionality assumption is theoretically weak and empirically leads to a carbon footprint distribution that can be very far off our best estimate. More work is needed to fully assess the consequences of its violation on the distribution of the carbon footprint. The consequences appear especially acute at the tails of the income distribution, where biases of the spending method are very likely large. One should therefore be cautious about estimates of carbon footprint of small groups when the spending method is used and these possible biases are not corrected for.

In order to compute more reliable distributions of the carbon footprint, we point the need to improve datasets in order to gather sufficiently detailed physical data rather than only spending data, or even worse only income data. This includes data in physical units (kilograms, liters, units) of the quantities of goods and services consumed, or alternatively, detailed unit prices to infer quantities from expenditures. Ideal datasets should also include the CB emissions per physical unit of each good (André et al. (2023) expand on that issue). To do so, we face three difficulties:

- First, data should be associated with socioeconomic variables in order to observe how the heterogeneity in prices and physical quantities correlates with various social dimensions (incomes, locations, socio-professional categories, age profile, etc.). One possibility would be to include these quantity variables in existing income and expenditures surveys. But these surveys already include a large number of variables, so such a move may be costly for statistical agencies and may reduce the rate and quality of response. Another possibility would be to rely on other sources of data on consumption, or new surveys dedicated to distributing the carbon footprint for different categories of households.

- Second, the CB emissions of products should also be available and reliable. The production of these data requires a deep analysis of production and distribution processes. Currently, they are not available for a large number of items and, when available, their reliability can be questioned. For instance, we observed some significant updates in the CB emissions of some specific oils, from the version 3.0 to 3.1 of the French Agribalyse dataset, however with small implications on the results and without changing the conclusions. One possibility would be an accounting framework and an information system so that firms could compute the CB emissions of their product as readily as they compute their production costs. The costs involved in compiling this information must be weighed against the benefits for society as a whole, which extend far beyond the mere quantification of the carbon footprint distribution.

- Third, the aggregation bias may remain important, in particular if insufficient detail is available for product varieties with different CB emissions and non homogeneous distribution in the population.

The carbon footprint contributes to frame the ethical and political discussions on the ecological transition and the computation of the carbon footprint of individuals and social groups participates to this framing. In recent years, highly publicised figures have focused the debate on GHG emissions by income groups, especially highlighting the responsibility of the rich people.[25] In a given national context, correcting for the estimation biases highlighted in this article would tend to narrow a little the carbon footprint gap between rich and poor and thus moderate this vision of a perfect alignment of the distribution of ecological responsibilities with the distribution of income. As the energy transition means reducing massively the emissions of the whole population, it will affect all households consuming carbon-intensive products. Underestimating the carbon footprint of low-income households may lead to underestimating their efforts, directly with carbon price increases, or indirectly with regulations or other behavioral changes in consumption targeted at products with high CB emissions. Our study puts forward evidence that there is no one-to-one relationship between income and carbon footprint. This is particularly important at the lower end of the income distribution, where many households are carbon dependent, sometimes intensively so.

Beyond that, the carbon footprint distributions figures are not sufficient to frame the discussions relative to the GHG transition. In particular they should not be viewed as representing the "carbon responsibility" of the (group of) households: a consumer does not have the authority on all the levies actionable to reduce GHG emissions, in particular on the production processes and the collective component of emissions (Liu, 2015; Pottier et al., 2020). Many other conventions for attributing emissions can be used to illustrate various conceptions of responsibility (Tukker et al., 2020). A relevant line of research would be to calculate different emissions distributions according to this wider range of attribution principles (see Pottier and Le Treut (2023) for a distribution of income-based emissions). The continued task of specifying the biases in distributing GHG emissions remains relevant for all allocation principles.

Our analysis of the estimation biases is also relevant for examining the distributions along other important socioeconomic and ecological dimensions. In particular, other social distinctions than income are particularly important in terms of public discussions and policies: for instance the locations of households which have a great impact on the availability of alternatives to reduce emissions (public transport, renewable energy network, local food, etc.). Socio-professional categories, age cohorts or rural-urban groups also define different consumption patterns, dependencies and lifestyles. These "horizontal inequalities" are particularly important, to evaluate the distributional impacts of en-

[25]For instance, the Oxfam report by Kartha et al. (2020), who miscalibrate the income elasticity of carbon footprint, see the discussion in Pottier (2022).

ergy transition policies, like carbon prices (Pottier et al., 2020; Douenne, 2020; Malliet, 2020). It is crucial for the identification of the most vulnerable households and for targeting the accompanying measures. Calculating inequalities in emissions along these other social dimensions will encounter the same sources of bias and the same observation issues. The collection of physical data to correct these biases will also allow the calculation of the distributions of other environmental impacts and contributions (pressure on land, water and material resources, recycling, etc.).

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# A Decomposition of the gap between the true carbon footprint and the imputed

Recall from eq. (1) that

$$CF^{h,k}_{\text{true}} = \sum_{i\in k} f_i q_i^h$$

and from eq. (2)

$$CF^{h,k}_{\text{imputed}} = e_k \sum_{i\in k} p_i^h q_i^h \,.$$

The ratio of the imputed and the true carbon footprint can be decomposed as:

$$\frac{CF^{h,k}_{\text{true}}}{CF^{h,k}_{\text{imputed}}} = \frac{\sum_{i\in k} f_i q_i^h}{e_k \sum_{i\in k} p_i^h q_i^h} \tag{7}$$

$$= \left(\frac{\sum_{i\in k} P_i q_i^h}{\sum_{i\in k} p_i^h q_i^h}\right)\left(\frac{\sum_{i\in k} f_i q_i^h}{e_k \sum_{j\in k} P_j q_j^h}\right) \tag{8}$$

$$= \left(\frac{\sum_{i\in k} P_i q_i^h}{\sum_{i\in k} p_i^h q_i^h}\right)\left(\sum_{i\in k} \frac{f_i}{e_k P_i}\frac{P_i q_i^h}{\sum_{j\in k} P_j q_j^h}\right) \tag{9}$$

$$= \left(\frac{\sum_{i\in k} P_i q_i^h}{\sum_{i\in k} p_i^h q_i^h}\right)\left(1+\sum_{i\in k} \left(\frac{f_i}{e_k P_i}-1\right)\cdot\frac{P_i q_i^h}{\sum_{j\in k} P_j q_j^h}\right) \tag{10}$$

$$= \left(\frac{\sum_{i\in k} P_i q_i^h}{\sum_{i\in k} p_i^h q_i^h}\right)\left(1+\sum_{i\in k} \left(\frac{f_i}{e_k P_i}-1\right)\cdot\left(\frac{P_i q_i^h}{\sum_{j\in k} P_j q_j^h}-\frac{P_i Q_i}{\sum_{j\in k} P_j Q_j}\right)\right) \tag{11}$$

with $Q_i = \sum_h q_i^h$ the total quantity of good $i$ consumed by all households, and $P_i Q_i = \sum_h p_i^h q_i^h$ the mean prices. We also assumed to obtain the last equation that:

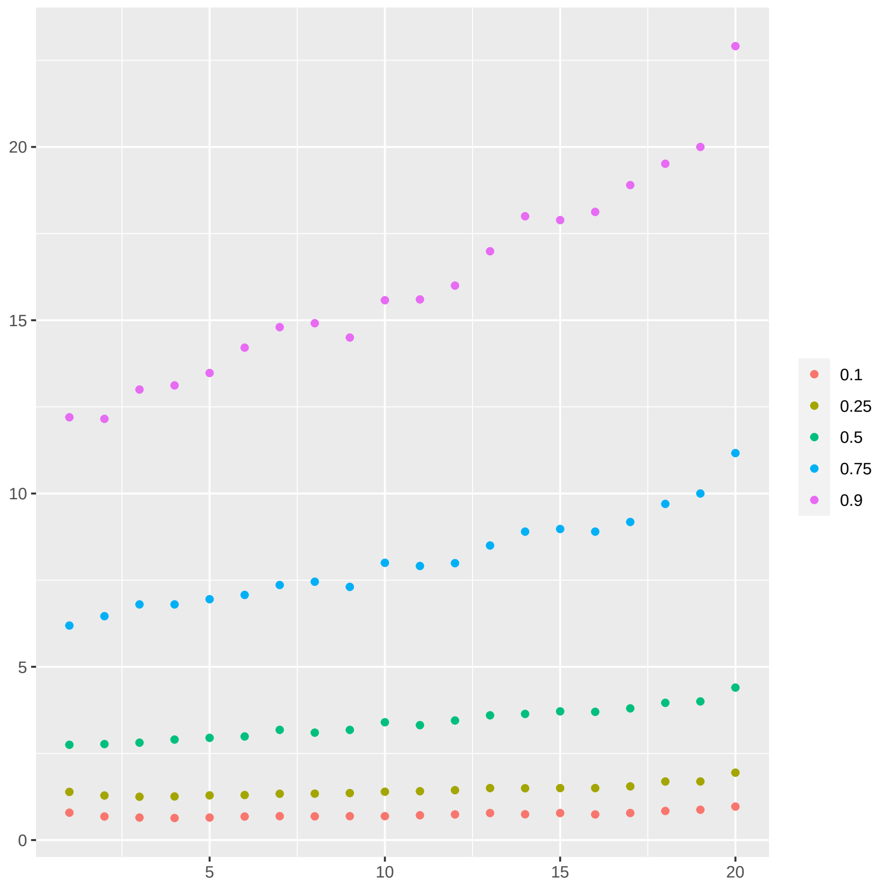
$$\sum_{i\in k} f_i Q_i = e_k \sum_{i\in k} P_i Q_i. \tag{12}$$

this condition simply means that consumption-based emissions $f_i$ and carbon intensity $e_k$ of spending are compatible in the sense that they give the same aggregate amount of consumption-based emissions from goods of category $k$.[26]

# B The price effet: supplementary results and data

[26]When this compatibility condition is not fulfilled, it introduces a systematic error, due to the gap between the carbon intensity used and the correct carbon intensity (the one that would fulfill the compatibility condition). This systematic error is however the same for all households: it impacts the level of the carbon footprint of category $k$, but not the distribution of the carbon footprint between households.

Figure B.1: Distribution of the prices by ventile of equivalized income, on common products




**Notes:** This Figure plots the percentiles 10, 25, 50, 75 and 90 of the distribution of prices for each ventile of equivalized income. It reproduces Figure 1 on the set of products that are bought by at least one household in each ventile. 291 816 observations on 403 products.

**Sources:** BdF 2017 ; authors' calculation.

Table 6: Consumption-based emissions of wine, rice and juices

| Product name in Budget des Familles | Product name in Agribalyse | CB emissions | Quality index |
|---|---|---|---|
| Fruit juice | Apple juice, pure juice | 0.50 | 2.38 |
| Fruit juice | Apricot nectar | 0.33 | 2.06 |
| Fruit juice | Banana nectar | 0.47 | 2.11 |
| Fruit juice | Fruit juice, mixed - apple base, standard | 0.73 | 2.04 |
| Fruit juice | Grape juice, pure juice | 0.45 | 2.04 |
| Fruit juice | Grapefruit juice, pure juice | 1.00 | 2.09 |
| Fruit juice | Lemon juice, pure juice | 0.79 | 1.95 |
| Fruit juice | Mango juice, fresh | 0.48 | 2.11 |
| Fruit juice | Mango nectar | 0.60 | 2.11 |
| Fruit juice | Mixed fruits juice, orange based, multivitamin | 1.08 | 2.02 |
| Fruit juice | Mixed fruits juice, pure juice | 0.91 | 3.11 |
| Fruit juice | Mixed fruits juice, pure juice, multivitamin | 0.91 | 3.11 |
| Fruit juice | Mixed fruits juice, reconstituted from a concentrate, multivitamin | 0.91 | 3.11 |
| Fruit juice | Mixed fruits nectar | 0.91 | 3.68 |
| Fruit juice | Mixed fruits nectar, multivitamin | 0.91 | 3.68 |
| Fruit juice | Mixed red fruits juice, pure juice | 0.63 | 2.04 |
| Fruit juice | Orange juice, home-made | 0.91 | 2.27 |
| Fruit juice | Orange juice, reconstituted from a concentrate | 1.10 | 2.02 |
| Fruit juice | Orange nectar | 0.78 | 2.05 |
| Fruit juice | Peach nectar | 0.93 | 2.06 |
| Fruit juice | Pear nectar | 0.82 | 2.11 |
| Fruit juice | Pineapple juice, pure juice | 6.51 | 2.14 |
| Fruit juice | Pineapple juice, reconstituted from a concentrate | 4.72 | 2.14 |
| Rice | Basmati rice, raw | 4.10 | 3.30 |
| Rice | Rice, brown, raw | 2.76 | 3.30 |
| Rice | Rice, mix of species (white, wholegrain, wild, red,etc.), raw | 2.76 | 3.30 |
| Rice | Rice, parboiled, raw | 2.76 | 3.61 |
| Rice | Rice, raw | 2.76 | 3.30 |
| Rice | Rice, red, raw | 2.76 | 3.30 |
| Rice | Wild rice, raw | 2.76 | 3.30 |
| Wine | Wine, red | 1.19 | 3.18 |
| Wine | Wine, rose | 1.19 | 2.69 |
| Wine | Wine, white, dry | 1.23 | 3.01 |
| Wine | Wine, white, sweet | 1.10 | 3.01 |

**Notes:** The consumption-based GHG emissions are measured in kg $CO_2$ per *kg* of product. The quality index provides an evaluation of the quality of this CB emissions (1: excellent; 5: very low). For some products, Agribalyse producers consider that the production processes are sufficiently similar to provide the same CB emissions.
**Notes:** Agribalyse 3.1

# C The price effect: a back-of-the-envelope estimate of its magnitude on the whole consumption basket

## C.1 Theory

Recall that the carbon footprint imputed from the expenditures for all the $i$ subvarieties in a $k$ category for household $h$ (or a group of households) is (equation (2)):

$$CF^{h,k}_{imputed} = e_k \sum_{i \in k} p^h_i q^h_i$$

The household's share of the $k$ national carbon footprint is equal to its share in expenditure:

$$\frac{CF^{h,k}_{imputed}}{\sum_h CF^{h,k}_{imputed}} = \frac{\sum_{i \in k} p^h_i q^h_i}{\sum_h \sum_{i \in k} p^h_i q^h_i}$$

From equation (5), $\frac{p^h_i}{Income_h^{a_i}}$ may be interpreted as some sort of average price for product $i$, corrected for the tendency of richer households to buy products at higher prices. The carbon footprint corrected for the price effect can then be written as:

$$CF^{h,k}_{price-corrected} = g_k \sum_{i \in k} \frac{p_i^h}{Income_h^{a_i}} q_i^h$$

with $Income_h^{a_i}$ the income of household (or group of households) $h$, raised to the power of $a_i$, the elasticity of the price with respect to revenues (see equation (5)), and

$$g_k = e_k \frac{\sum_h \sum_{i \in k} p_i^h q_i^h}{\sum_h \sum_{i \in k} \frac{p_i^h}{Income_h^{a_i}} q_i^h}$$

which ensures that $\sum_h CF^{h,k}_{imputed} = \sum_h CF^{h,k}_{price-corrected}$ for any $k$ category, i.e. the same national carbon footprint is distributed between households using both approaches.

Seen from another angle, the household's share of the national carbon footprint of $k$ would be equal, after correction for the price effect, to the household's share of national expenditure *if the household had paid some sort of average price for each of the products*:

$$\frac{CF^{h,k}_{price-corrected}}{\sum_h CF^{h,k}_{price-corrected}} = \frac{\sum_{i \in k} \frac{p_i^h}{Income_h^{a_i}} q_i^h}{\sum_h \sum_{i \in k} \frac{p_i^h}{Income_h^{a_i}} q_i^h}$$

## C.2 Data

The 2022 carbon footprint of households consumption, broken down by 64 NAF branches,[27] is converted to 38 COICOP functions. For each of these 38 functions, the national carbon footprint is distributed by living standard deciles of households according to their share in aggregate spendings in 2017.[28]. We use the average in each decile of the standard of living of households to correct for the price effect.[29] In accordance with section 4, we choose $a_i = 0,19$.[30]

For the GHG directly emitted by households, we distribute the national aggregates for 2022 according to the share by each decile in these emissions.[31] Given that they are computed with quantity data, the GHG directly emitted by households are the same in the carbon footprint and its version corrected for the price effect.

## C.3 Results

Figure C.2 provides the average carbon footprint in each decile, for the carbon footprint imputed with spendings, and its correction for the price effect on all products. The price effect leads to an underestimation of the carbon footprint for

[27] SDES, 2023, https://www.statistiques.developpement-durable.gouv.fr/lempreinte-carbone-de-la-france-de-1995-2022?rubrique=27&dossier=1286

[28] *Comptes des ménages par catégorie*, year 2017, Insee

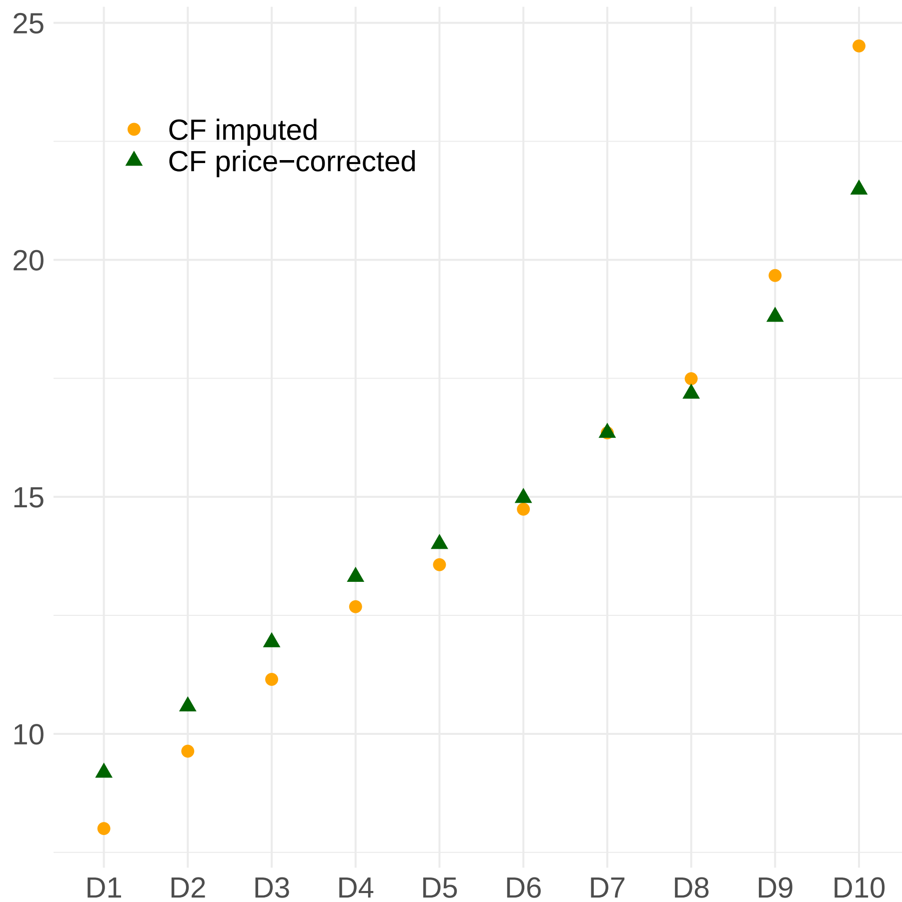
[29] *Revenus et Patrimoine des ménages*, year 2018, 2021 edition, Insee

[30] Another possibility would be to use elasticities differentiated by product.

[31] Prometheus model (CGDD)

the bottom 6 deciles, by up to 13% in the bottom decile, and an overestimation for the 3 upper deciles, by up to 14% in the top decile.

Figure C.2: Carbon footprint imputed with spendings (orange) or corrected for the price effect (green), average in each decile of households (in tonnes of equivalent $CO_2$)

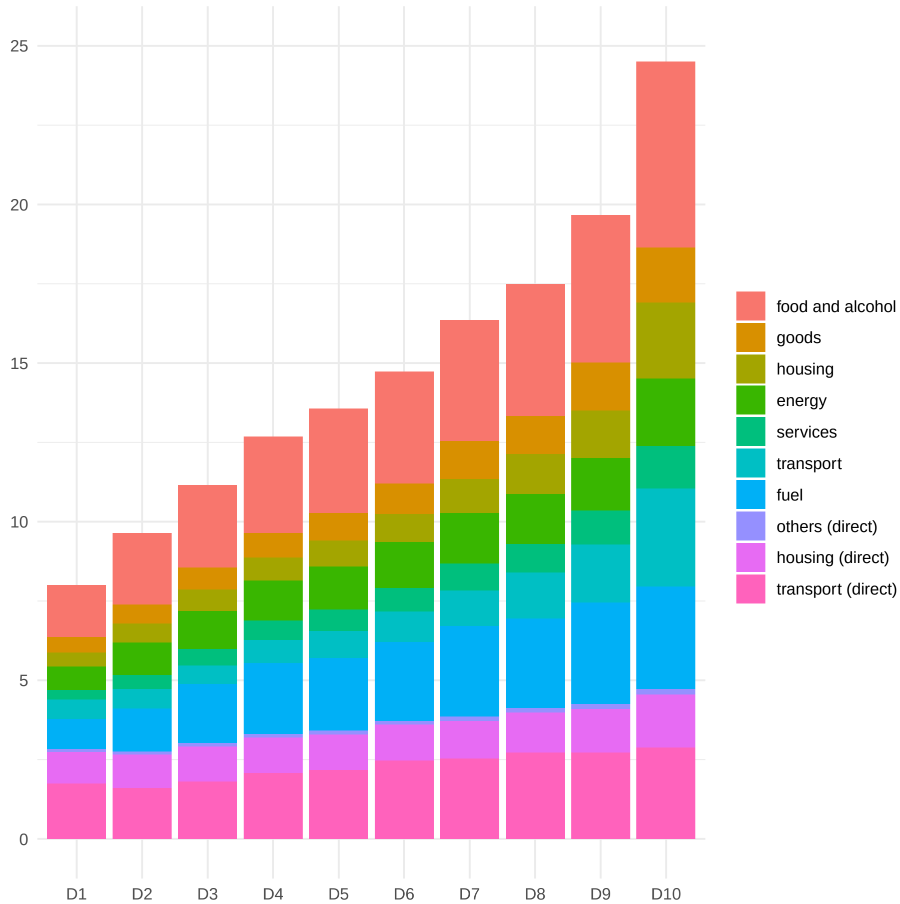



**Notes:** The carbon footprint imputed with spending stands at 8.0 tonnes of $CO_2$ equivalent for an average household in the bottom decile. Correcting for the price effect leads to a carbon footprint at 9.2 tonnes.

**Sources:** Insee, Family Budget Survey 2017 and National Accounts 2017, 2018; CGDD, Prometheus model; SDES, carbon footprint 2022, 2023; authors' calculations.

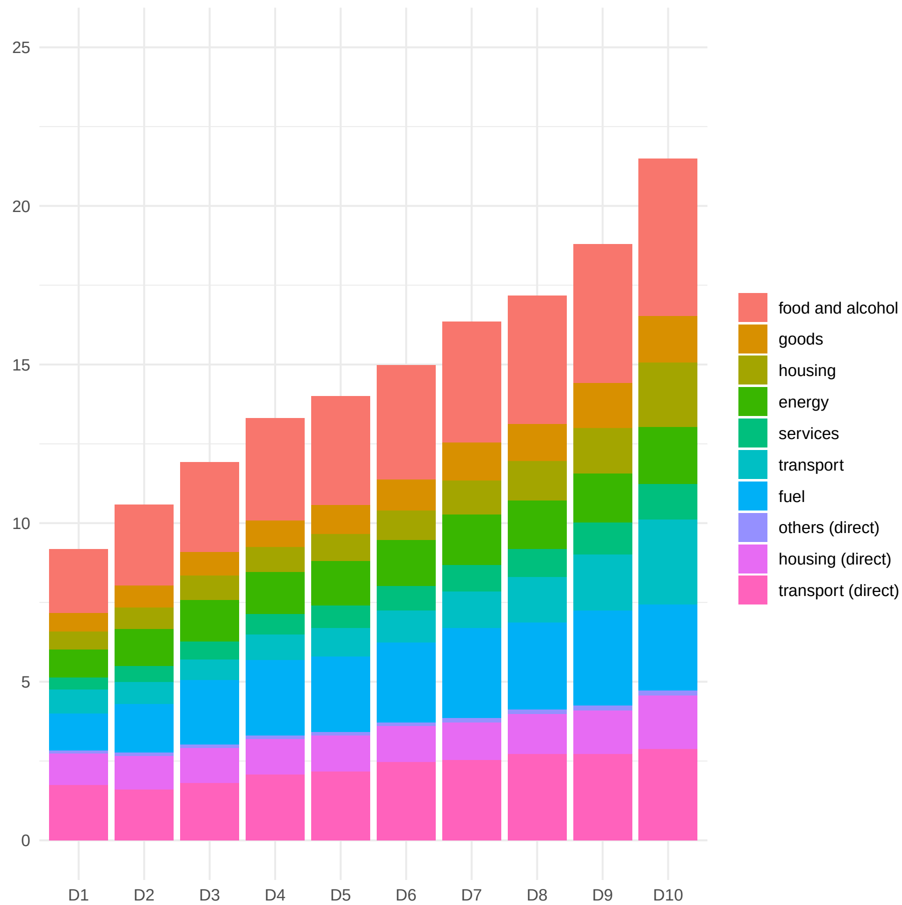
Figures C.3 and C.4 break down these two approaches by categories of products, defined in Table 7.

Figure C.3: Breakdown of the carbon footprint imputed with spendings, average in each decile of households (in tonnes of equivalent $CO_2$)




**Sources:** Insee, Family Budget Survey 2017 and National Accounts 2017, 2018; CGDD, Prometheus model; SDES, carbon footprint 2022, 2023; authors' calculations.

Figure C.4: Breakdown of the carbon footprint imputed with spendings and corrected for the price effect, average in each decile of households (in tonnes of equivalent $CO_2$)




**Sources:** Insee, Family Budget Survey 2017 and National Accounts 2017, 2018; CGDD, Prometheus model; SDES, carbon footprint 2022, 2023; authors' calculations.

Table 7: Definition of the goods and services categories used in Figures C.3 and C.4

| COICOP | Detailed label (French) | Category |
|---|---|---|
| 011 | Produits alimentaires | food and alcohol |
| 012 | Boissons non alcoolisées | food and alcohol |
| 021 | Boissons alcoolisées | food and alcohol |
| 022 | Tabac | goods |
| 031 | Articles d'habillement | goods |
| 032 | Chaussures y.c réparations | goods |
| 041 | Loyers d'habitations effectifs | housing |
| 042 | Loyers imputés | housing |
| 043 | Réparation et entretien courants de logements | housing |
| 044 | Autres services liés au logement | housing |
| 045 | Electricité, gaz et autres combustibles | energy |
| 051 | Meubles, art. d'ameublement, tapis et autres | housing |
| 052 | Articles de ménage en textile | housing |
| 053 | Appareils ménagers | housing |
| 054 | Verrerie, vaisselle et ustensiles de ménage | housing |
| 055 | Outillage et autres matériels pour la maison et le jardin | housing |
| 056 | Biens et services pour l'entretien courant de l'habitation | housing |
| 060 | Santé | services |
| 071 | Achats de véhicules | transport |
| 072 | Dépenses d'utilisation de véhicules | fuel |
| 073 | Services de transports | transport |
| 08 | Communications | services |
| 091 | App. et acc. audio-visuels et informatiques | goods |
| 092 | Autres biens durables culturels et récréatifs | goods |
| 093 | Autres biens et équipements de loisirs | goods |
| 094 | Services culturels et récréatifs | services |
| 095 | Presse, livres et papeterie | goods |
| 096 | Voyages touristiques tout compris | services |
| 100 | Education | services |
| 111 | Restauration | food and alcohol |
| 112 | Services d'hébergement | housing |
| 121 | Soins personnels | goods |
| 123 | Effets personnels n. c. a. | goods |
| 124 | Action sociale | services |
| 125 | Assurances | services |
| 126 | Services financiers | services |
| 127 | Autres services | services |
| Em dir Logement | Émissions directes logement | housing (direct) |
| Em dir Transport | Émissions directes Transport | transport (direct) |
| Em dir autres | Émissions directes autres | others (direct) |

# D Details of the data on oils in the different sources

The classification of the 2017 household budget survey includes two items dedicated to the purchase of edible oils: olive oil (item 01153) and peanut, sunflower, corn and rapeseed oil (item 01154). However, analysis of the diaries and comparison with the Nielsen data indicates that this separation was interpreted by the respondents as 'olive oils' and 'other oils'.

## D.1 Matching Nielsen and Agribalyse

The Nielsen dataset aims at covering all cooking oils consumption and includes the following oils: peanut oil, argan oil, rapeseed oil, frying oil, mixed 4 oils, hazelnut oil, walnut oil, olive oil, grapeseed oil, sesame oil, soybean oil, sunflower oil, and a 'other oils' item.

Agribalyse's CB emissions data include the following items: combined oil (oil blend), combined oil, olive oil and seed blend, peanut oil, rapeseed oil, cottonseed oil, flaxseed oil, corn oil, hazelnut oil, refined palm oil, palm oil, unspecified, grape seed oil, sesame oil, soybean oil, sunflower oil, extra virgin olive oil, frying oil, unspecified, as well as a fat or solid vegetable fat (margarine type) for frying. It is noted that some oils are not necessarily directly for final household consumption but rather for intermediate use by the food industry (such as palm oil).

The nomenclature items of Nielsen overlap with those from Agribalyse except for three items: argan oil, nut oils, and the item 'uncategorized oils'. The first two represent 0.54% of total oil consumption according to Nielsen database. Without explicit CB emissions for them, we exclude them from the analysis. The item 'uncategorized oils' of Nielsen represents 1.6% of total oil consumption and is presumably composed of oils that are in the Agribalyse dataset (such as linseed oil or maize oils). As its composition is not detailed in Nielsen and its consumed quantities is negligible in aggregate, we also drop this item from the analysis. We therefore consider in a broad sense that the 'other oils' item in the 2017 household budget survey is composed of the following nine oils: peanut oil, rapeseed oil, frying oil, combination oil (oil blend), hazelnut oil, grape seed oil, sesame oil, soybean oil, and finally sunflower oil (see Table 2). These items, together with extra virgin olive oil represent 97.9% of the quantities of oils sold in France in 2017 to households according to the Nielsen Institute, and have a carbon emission rate (in kg $CO_2$/kg of product) within the Agribalyse data of Ademe.

## D.2 Integrating Nielsen and BdF

The household budget survey BdF 2017 has oil consumption data in quantities alongside monetary purchase data, as does the Nielsen panel source. From BdF 2017, we find a total quantity of 288.5 millions of total oil consumption in 2017 (resp. 86 millions for olive oils) and a mean price of 3.92 € (resp. 7.88 € for olive oil). From Nielsen, total oil consumption is measured at 282.3 millions of liters with a mean price of 3.23 € in 2017 (resp. 72.2 millions of liters and 6.76 € for olive oils). These comparisons were made on the full scope of each source, which aims to cover all oils consumed by households. The scopes are however non identical.

The Nielsen data allow us to break down the “other oils” item in HBS into 9 sub-items for which we have quantities and average prices in the Nielsen data, and CB emissions data (in kg $CO_2$/kg of product) in the Agribalyse data (see above subsection). The total quantities consumed are not directly fully compatible with each other and require the HBS and Nielsen data to be made consistent.

We keep price and quantity data from BdF for “olive oil” and the aggregate “other oils”. For the nine oils that composed the “other oils” category, the Nielsen quantity data are proportionally scaled in order to reach the “other oils” quantity aggregate of BdF 2017, the price data is also scaled to reach average price of BdF 2017. In short, for the “other oils” category, we use total quantity and average price from BdF 2017, and within the “other oils” category, we use relative quantities and relative prices from Nielsen.

## D.3 Distributing oils to households

We therefore have on the one hand a ’true’ breakdown by type of oil, but only for the aggregate consumption, i.e. without knowing the types of households that consume these oils, and on the other hand the less detailed HBS source which only has a “other oils” item but benefits for this item from a breakdown by type of household. These degrees of freedom make it possible to test different hypothetical distributions within the types of households for oil purchases broken down by detailed oil, as explained in 5.2.

In polar case 1, CB emissions of oils decrease with increasing quantiles. That is most emitting oils (in terms of CB emissions kg $CO_2$ /kg of product) are allocated to the bottom quintile. More precisely, hazelnut oil, peanut oild, rapeseed oil, and sesame oil are allocated fully to Q1; combined oil is allocated between Q1 and Q2; various frying and soy oil are allocated fully to Q2; sunflower oil is allocated between Q2, Q3, Q4, and Q5; grapeseed oil is allocated to Q5.

In polar case 2, CB emissions of oils increase with quantiles. That is most emitting oils (in terms of CB emissions kg $CO_2$/kg of product) are allocated first to the top quintile. More precisely, hazelnut oil, peanut oild, rapeseed oil, and sesame oil are allocated fully to Q5; combined oil is allocated between Q5, Q4, and Q3; various frying and soy oil are allocated fully to Q3; sunflower oil is allocated between Q3, Q2, and Q1; grapeseed oil is allocated to Q1.

The simulations that are carried out consist firstly of randomly distributing the quantities of oil consumed by income quintile and by type of oil, and secondly of calibrating these data on the margin (biproportional RAS) so that the aggregate information on the total quantities of oil by type of oil is respected, as well as the total quantities consumed by income quintile. There are an infinite number of possible crossings, so we run 1000 simulations and then determine a 5% compatibility interval for the footprint of each income quintile in a non-parametric way by removing the 2.5% of the lowest and highest amounts.

# E Details of analysis of cooking oils

## E.1 Formulas for the analysis of cooking oils

In subsection 5.1, we assume that there is no further carbon intensity heterogeneity among the different kinds of oils in the "other oils" category. We have two CB emissions $f_{\text{olive}}$, $f_{\text{others}}$, for olive oil category and "other oils" category, coming from the combination of Agribalyse and Nielsen dataset, as explained in the main text. For each household group $h$, the HBS provides quantities of the two categories, $q^h_{\text{olive}}$ and $q^h_{\text{others}}$, and spending on the two categories (decomposed here as quantities times price) $p^h_{\text{olive}} q^h_{\text{olive}}$ and $p^h_{\text{others}} q^h_{\text{others}}$

We introduce three methods to reconstruct the carbon footprint $CF^h$ of household $h$ due to the consumption of cooking oils: the quantity method (denoted qu.), the spending method (denoted sp.), and the disaggregated spending method (denoted dis. sp.).

The formulas for the methods are the following:

$$CF^h_{\text{qu.}} = f_{\text{olive}} q^h_{\text{olive}} + f_{\text{others}} q^h_{\text{others}} \tag{13}$$

$$CF^h_{\text{sp.}} = e_{\text{oils}} \left( p^h_{\text{olive}} q^h_{\text{olive}} + p^h_{\text{others}} q^h_{\text{others}} \right) \tag{14}$$

$$CF^h_{\text{dis.sp.}} = e_{\text{olive}} p^h_{\text{olive}} q^h_{\text{olive}} + e_{\text{others}} p^h_{\text{others}} q^h_{\text{others}} \tag{15}$$

The carbon intensities are computed thanks to the compatibility condition (4), that ensures the carbon footprint aggregated over all households is the same for all methods:

$$e_{\text{olive}} = f_{\text{olive}} \sum_h q^h_{\text{olive}} / (\sum_h p^h_{\text{olive}} q^h_{\text{olive}}) \tag{16}$$

$$e_{\text{others}} = f_{\text{others}} \sum_h q^h_{\text{others}} / (\sum_h p^h_{\text{others}} q^h_{\text{others}}) \tag{17}$$

$$e_{\text{oil}} = \left( f_{\text{olive}} \sum_h q^h_{\text{olive}} + f_{\text{others}} \sum_h q^h_{\text{others}} \right) / \left( \sum_h p^h_{\text{olive}} q^h_{\text{olive}} + p^h_{\text{others}} q^h_{\text{others}} \right) \tag{18}$$

The gap between the carbon footprint computed with the quantity method and the spending method is decomposed according to formula (3), which thus is specified for a household $h$ (or a group of households by summing the quantities and spending of the members of the group) as:

$$\frac{CF^h_{\text{qu.}}}{CF^h_{\text{sp.}}} = \left(\frac{P_{\text{olive}} q^h_{\text{olive}} + P_{\text{others}} q^h_{\text{others}}}{p^h_{\text{olive}} q^h_{\text{olive}} + p^h_{\text{others}} q^h_{\text{others}}}\right) \tag{19}$$
$$\cdot \left( \begin{array}{l} 1 + \left(\frac{f_{\text{olive}}}{e_{\text{oil}} P_{\text{olive}}} - 1\right) \cdot \left(\frac{P_{\text{olive}} q^h_{\text{olive}}}{P_{\text{olive}} q^h_{\text{olive}} + P_{\text{others}} q^h_{\text{others}}} - \frac{P_{\text{olive}} Q_{\text{olive}}}{P_{\text{olive}} Q_{\text{olive}} + P_{\text{others}} Q_{\text{others}}}\right) \\ + \left(\frac{f_{\text{others}}}{e_{\text{oil}} P_{\text{others}}} - 1\right) \cdot \left(\frac{P_{\text{others}} q^h_{\text{others}}}{P_{\text{olive}} q^h_{\text{olive}} + P_{\text{others}} q^h_{\text{others}}} - \frac{P_{\text{others}} Q_{\text{others}}}{P_{\text{olive}} Q_{\text{olive}} + P_{\text{others}} Q_{\text{others}}}\right) \end{array} \right)$$

The first factor is the price effect, the second the carbon intensity effect, (the inverse of) both being reported in Table 3. In the formula above, to ease notations, we have introduced $Q_{\text{olive}} = \sum_h q^h_{\text{olive}}$ and $P_{\text{olive}} = \sum_h p^h_{\text{olive}} q^h_{\text{olive}} / Q_{\text{olive}}$, and correspondingly for "others". All these numbers are computed only from the HBS data.

Note that from the definitions, we have $f_{\text{olive}}/P_{\text{olive}} = e_{\text{olive}}$, and correspondingly for "others".

The ratio of the true carbon footprint and the disaggregated spending one is given by:

$$\frac{CF^h_{\text{qu.}}}{CF^h_{\text{dissp.}}} = \left(\frac{\frac{e_{olive}}{e_{oil}} P_{\text{olive}} q^h_{\text{olive}} + \frac{e_{others}}{e_{oil}} P_{\text{others}} q^h_{\text{others}}}{\frac{e_{olive}}{e_{oil}} p^h_{\text{olive}} q^h_{\text{olive}} + \frac{e_{others}}{e_{oil}} p^h_{\text{others}} q^h_{\text{others}}}\right) \tag{20}$$

## E.2 Decomposition of the gap between (estimated) true and imputed carbon footprint

Table 8: Decomposition of the gap between the true and the imputed carbon footprint into the price and the carbon intensity effects - median of 1000 random draws

| | Q1 | Q2 | Q3 | Q4 | Q5 |
|---|---|---|---|---|---|
| $CF_{\text{imputed}}/CF_{\text{true}}$ | 0.65*** | 0.78*** | 0.96** | 1.20*** | 1.61*** |
| price effect | 0.83*** | 0.89*** | 0.96* | 1.04 | 1.24*** |
| intensity effect | 0.79*** | 0.87*** | 1.00 | 1.15*** | 1.30*** |

**Notes:** For figures with *, ** or ***, 1 is outside the interval between the percentiles 5 and 95, 2.5 and 97.5, and 0.5 and 99.5 respectively, of 1000 random draws for the allocation of the different kinds of other oils. See notes of Table 3.

**Sources:** BdF 2017, Agribalyse 3.1, Nielsen 2017 ; authors' calculation

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