Unravelling the Influence of Household Characteristics and Decisions on their Carbon Footprint: A Quantile Regression Analysis

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Abstract – This study uses data from the 2017 French Household Budget Survey (*Enquête Budget de famille*) and an input-output model to examine the carbon footprint distribution of French households. Using multivariate nested models and quantile regression techniques, it explores disparities in households carbon footprints stemming from socioeconomic characteristics (e.g., size, age, education), income, or household decisions (e.g., home energy source, dwelling type, car ownership). The findings show that the three dimensions are crucial for understanding carbon footprint differences. Other characteristics being equal, education, age and household size, influence carbon emissions. Household decisions also have great explanatory power, especially at the bottom of the distribution, while the type of urban unit (urban/peri-urban/rural) has no significant influence on carbon emissions.

JEL: D12, Q56, R15, C21
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In 2019, the French government enacted the Energy and Climate Law[1] (*Loi énergie-climat*), one of the aims being to achieve the net zero emissions (NZE) target set by the European Union for 2050. This ambitious plan aims to reduce France's fossil fuel consumption by 40% compared to 2012. While the energy sector is expected to make significant contributions to promote sustainable production, there is increasing emphasis on the "citizen-consumer" concept, which places individuals at the heart of this transition (Rumpala, 2009). Household consumption generates GHG emissions both directly (e.g., driving a diesel vehicle) and indirectly (e.g., eating meat), contributing to their carbon footprint. Beyond its unambiguous use in environmental accounting, this conventional indicator also reflects two additional dimensions of the environmental transition: liability and vulnerability. The liability aspect highlights how varying household consumption patterns create different environmental pressures. In this context, households with the greatest carbon footprints should drastically reduce their emissions since they bear relatively more responsibility for global warming and have the highest potential for GHG emission abatement. Furthermore, the household's carbon footprint can determine its relative exposure to increasing energy prices induced by carbon pricing policies. Favoring sustainable consumption can be costly and socially challenging due to distributive effects. When formulating environmental strategies, policymakers should balance the costs and benefits of the transition by considering these aspects.

These considerations emphasize the importance of initiating an inclusive transition, as carbon footprints are typically unevenly distributed across households (Chancel & Piketty, 2015). Two main sources of inequality should be considered to explain carbon footprint disparities. As a consequence of the intertwined relationship between carbon emissions and consumption levels, income inequality explains much of the unequal carbon footprint distribution (Weber & Matthews, 2008; Duarte *et al.*, 2012; Büchs & Schnepf, 2013; Nässén, 2014; Christis *et al.*, 2019; Sager, 2019; Pottier *et al.,* 2020; Lévay *et al.,* 2021). Economists have typically analyzed this vertical dimension of inequality by examining the income or expenditure elasticity of carbon footprints (Lenzen, 1998; Büchs & Schnepf, 2013). If it is generally accepted that looking at the distribution through the lens of income is a relevant procedure, emissions variability can also be important within same-income groups (Berry, 2019; Douenne, 2020; Pottier *et al.,* 2020). Socioeconomic and sociodemographic factors such as household size, education level, the age of the reference person, and geographic location can provide information about households' carbon footprints. These factors are associated with the horizontal dimension[2] of inequalities.

While many studies have confirmed the importance of these factors on households' carbon footprints, it is worth considering whether individual choices may also play a significant role in portraying emissions. For instance, we may wonder if the source of home energy or the type of dwelling can explain large variations in emissions. To some extent, we should determine which aspect is more closely associated with GHG emissions and, therefore, more relevant to understand carbon footprint inequality. If such a dichotomy between household characteristics and decisions may be irrelevant at first sight, it may be relevant for policymakers. In their quest for the optimal instrument, policymakers seek efficient levers to markedly reduce emissions. Although invariable attributes largely shape consumption habits, individual choices offer greater potential for initiating behavioral change due to their greater flexibility. Understanding these relationships could help policymakers to formulate environmental policies that target specific unsustainable behaviours while safeguarding the well-being of more constrained households.

Furthermore, in most cases, the studies of GHG emissions determinants have predominantly focused on the average effects of variables through ordinary least squares (OLS) regressions (Pottier, 2022). However, the effects can differ depending on the part of the distribution of the emissions under consideration. The sensitivity of carbon footprints to changes in specific characteristics may differ whether we are looking at its average or at the top or the bottom of the distribution, potentially leading to misleading results when only the average is considered. Therefore, we should investigate whether emission disparities arise from socioeconomic characteristics or decision variables and whether these factors exert the same level of influence across the entire distribution of emissions.

This study addresses this gap by employing an innovative approach to analyze the emissions distribution of French households. After estimating the carbon footprint of households

1. *https://www.ecologie.gouv.fr/loi-energie-climat*
2. *They contribute to carbon footprint inequalities between households of the same income group.*

using a hybrid methodology combining input-output tables and life cycle assessment, the first objective is to evaluate whether socioeconomic characteristics and choices remain significant in explaining carbon footprint inequality when income is controlled for. We use multivariate nested OLS regression models to discern how these factors effectively influence the carbon footprint of French households. Second, we employ quantile regression models to explore how these factors affect carbon footprints across distribution segments. Comparing these results with mean estimates highlights potential misconceptions about emissions across different dimensions. Previous research by Han *et al.* (2015) specifically examined household carbon footprints in China using quantile regression models. Their findings support the potential different impacts of characteristics on different quantiles of emissions distribution, with potentially inversed impacts between the bottom and the top of the distribution.

This study is structured as follows: section 1 covers data, methodology, and some estimates of carbon footprint distribution. Section 2 reviews empirical findings from the literature and introduces the econometric models. Section 3 presents the econometric results, followed by a discussion of their implications, before the article concludes.

1. Households' Carbon Footprint Estimation

1.1. The Household Budget Survey

Data on household expenditures were sourced from the 2017 edition of the *Enquête Budget de Famille* (Household Budget Survey, BDF), conducted by the National Institute of Statistics and Economic Studies (INSEE). We focus on the 12,000 households residing in Metropolitan France. The survey spans six consecutive waves and captures the weekly consumption patterns of households. The sample is representative, devoid of seasonal effects, and calibrated to approximate national statistics. The survey provides information on household expenditures and resources. Expenditures are categorized into almost 250 items based on the five-digit Classification of Individual Consumption by Purpose (COICOP).

As remarked by Douenne (2020), fuel consumption may be overestimated for some households. While this variability between households decreases when considering aggregated expenditures, challenges remain when examining the distribution of fuel consumption within income groups. To address this potential issue, we complement the BDF survey with data from the *Enquête Mobilité des Personnes* (French Mobility Survey, EMP) of 2019. This survey, conducted by the *Service des Données et Études Statistiques* (Statistical Data and Studies Department, SDES), provides information on French households' trips and transportation habits as well as on their socioeconomic characteristics. To align the two datasets, we adopt a statistical methodology inspired by the work of Douenne (2020) and based on the method developed by D'Orazio *et al.* (2006). This methodology consists in matching households with the most similar characteristics possible. Using a non-parametric nearest neighbour distance (NND) hotdeck method, we match households based on income, type of urban unit, household type, number of vehicles, and consumption units. Once the trips made in kilometers are obtained, we transform them into expenditures using an expenditure per kilometer factor estimated at the income decile and type of urban unit (i.e., urban, peri-urban, rural) levels as in Douenne (2020). This ensures that expenditures remain relatively proportional to those reported in the original BDF survey.

In total, we consider around 230[3] expenditures at the COICOP level. We aggregate expenditures in eight categories to reflect the composition of the household carbon footprint properly while ensuring fair coverage of budget allocations across durables, non-durables goods, and services.

The eight categories are food, market services, non-market services, home energy, manufactured goods, transportation, cultural & entertainment, and construction. Food expenditures correspond to nutrition, tobacco, and beverage expenses. While market services include expenditures for hairdressing, cell phone contracts, insurance, and real estate services for instance, non-market services mainly cover education, health, and social protection expenses. Home energy expenses include mostly energy bills. Manufactured goods include durable and semi-durable goods such as textiles, furniture, new vehicles, and household appliances. Transportation comprises spending on fuels, mobility services, and equipment. Cultural & entertainment expenses relate to dining out, hotel stays, and cultural activities. Finally, construction expenditures encompass

3. Expenditures for rent, taxes, and subsidies are excluded due to the challenges involved in justifying and interpreting their embedded carbon emissions. Therefore, the total budget considered here may miss certain expenditures, notably for low-income households.

housing renovations and the construction of new buildings. We present the expenditures of French households in 2017 following our aggregated classification in the Online Appendix (see Table S1-1 – link at the end of the article).

1.2. Estimating the Carbon Footprint of Households

There are two main approaches to calculating embedded carbon emissions in consumption. The top-down approach uses national accounts and environmental extensions of input-output (EE-IO) tables. In contrast, the bottom-up approach estimates emissions at the product level using life cycle assessment (LCA). This second approach consists of a meticulous inventory of the energy and materials used throughout a product's value chain, in order to calculate the total emissions emitted during its production, use and disposal (Steubing *et al.*, 2022).

In this study, we combine the two methods: EE-IO for estimating indirect emissions and LCA for direct emissions. Household expenditures are linked to the carbon intensity of goods and services to derive total GHG emissions embedded in consumption. This synthetic method has been used in numerous studies to estimate households' carbon footprints at both the global (Lenzen *et al.*, 2006; Hubacek *et al.*, 2017a; 2017b; Bruckner *et al.*, 2022) and national levels (Baiocchi *et al.,* 2010; Renner, 2018; Malliet, 2020).

1.2.1. The Computation of Indirect Emissions

As a significant proportion of French households' carbon footprint is generated by imports, it is essential to incorporate multi-regional interdependencies in production. In this study, we rely on the multi-region input-output (MRIO) tables from Exiobase 3 (Stadler *et al.*, 2018) for 2017. Exiobase offers a comprehensive and integrated accounting framework of environmental metrics. Moreover, it provides a product-level disaggregation, which is more suitable for estimating the induced carbon footprint of consumption.

At its core, an input-output model is a system of linear equations, where each equation describes how an industry's output is distributed throughout the economy (Leontief, 1970). Consequently, input-output tables take the form of matrices, with rows indicating the distribution of a producer's output across all industries and columns indicating the composition of inputs required by a specific industry to produce its output. These flows are typically expressed in monetary terms (in million euros) at basic prices. Our specific input-output model consists of 200 products that fulfill the final demand of households, public administrations, and non-profit organizations for 44 countries and five rest of the world regions (i.e. a total of 49 regions).

The starting point of an input-output analysis is based on the monetary values of the flows of products from each sector (as a producer / seller) to each other (as a purchaser / buyer). The transactions between pairs of sectors (from sector i to sector j) are noted $z_{i,j}$. In other words, sector j's demand for inputs from other sectors is related to the number of goods and services produced by sector j over the same year. External sales to households, government, and foreign trade constitute the exogenous part of the model, which describes the total final demand. Assuming that we have 200 products for each of the 49 regions ($n = 9{,}800$), constituting the global economy, and if we denote by x the column vector of sectors' total output and by f the column vector of total final demand addressed to sectors, we can write the following standard equation:

$$x = Z1 + f$$

where 1 is the summation vector of size $n \times 1$. A fundamental assumption of the input-output model is the dependency between inter-sector flows and total production. These ratios refer to technical coefficients, expressed as $a_{i,j} = z_{i,j} / x_j$. The main objective of the input-output analysis is to determine the required output growth of each sector to meet final demand variations. Since final demand is exogenous, technical coefficients are constant, and total output is endogenous, we can represent the model in matrix form, as follows:

$$x = \left(I - A\right)^{-1} f$$

where I is the identity matrix of size $n \times n$ and A is the matrix of technical coefficients[4] of size $n \times n$. $L = \left(I - A\right)^{-1}$ forms the total requirement matrix, also known as the Leontief inverse. It gathers the amount of total output from sector i required to satisfy the final demand of sector j.

This standard framework can be extended to account for emissions flows between sector products (Lenglart *et al.*, 2010; Mardones & Muñoz, 2018). The environmental extension relies on a carbon accounting framework, which includes the amount of carbon dioxide equivalent[5] (CO_2e) emitted directly by each sector. Assuming a proportional relationship between

4. *In matrix form*: $A = Z\ diag(x)^{-1}$.
5. *We use the estimates of GHG emissions composed of seven gases transformed in carbon dioxide equivalent.*

total production and total emissions, we obtain the direct carbon intensity as $D_j^d = g_j / x_j$ where g_j captures the total absolute amount of direct emissions. D^d is a row vector of dimension n and expresses the tons of CO_2e (tCO_2e) emitted by the sector product j with respect to its total output (tCO_2e/€).

At this stage, these carbon intensities only consider the direct emissions of a particular sector to produce a good or service. However, the carbon emitted for producing a specific product also integrates upstream emissions, representing emissions from other sectors' products to produce a final good or service. To get the total (direct and indirect) carbon intensity of product j, we must include indirect emissions from input requirements. Therefore, the total emission intensities are represented by the following equation:

$$D^t = D^d \left(I - A\right)^{-1}$$

where D^t is a row vector of dimension n composed by total carbon intensities. For the purpose of our study, we consider only the carbon intensities of the 200 products consumed in France.

One difficulty of this analysis is to make legitimate correspondence between the budget survey and the final demand in the input-output model. In other words, we want to bridge macroeconomic aggregates with microeconomic estimates. Two main aspects must be considered here. First the correspondence between goods and services at the microeconomic level (expressed in COICOP) and the MRIO denomination. Secondly, as MRIO tables are expressed in basic prices and budget surveys at purchaser prices, price conversion should be performed[6] before multiplying households' expenditures with carbon intensities.

We use the concordance matrix[7] of Ivanova *et al.* (2017) to allocate aggregated expenditures of households (64 groups of expenditures) into the 200 products available in Exiobase. For some groups of expenditures, the allocation to a product is unambiguous since there is a perfect match between the two categories. However, it is also possible that one item corresponds to more than one product. Indeed, some expenditure items can be directly or indirectly linked to the production of several products. In this case, the concordance matrix splits expenditure into shares between several products.

For price conversion, we also rely on the work of Ivanova *et al.* (2017), which developed a methodology to transform consumption amounts into basic prices for Exiobase tables. We can convert price units using various trade statistics. This approach allows us to reallocate margins and taxes to their respective sectors, resulting in a "deflated final demand" at basic prices. Furthermore, this approach keeps the input-output framework at basic prices while not overestimating emissions from purchases.

Households' expenditures[8] are aggregated to match the 64 groups of expenditures. We create matrix B, which includes each household's budget allocated to the 64 expenditure groups. Then, we define a budget allocation matrix M of size 64×200, which is the concordance matrix between the group of 64 expenditures and sectors. We obtain the CO_2e emissions for the 200 groups of expenditures as follows:

$$E^{ind} = BM \cdot \operatorname{diag}\left(D_{FR}^t\right)$$

where D_{FR}^t is the row vector of dimension 1×200, describing the total carbon intensity of French sectors. Thus, the elements of E_h^{ind} depicts the indirect carbon emissions of household h that we sum following our product aggregation.

1.2.2. The Computation of Direct Emissions

While the previous methodology approximates the cradle-to-gate approach in carbon accounting, physical quantities consumed are generally better suited for estimating direct emissions (e.g., home energy and transport) as they relate to the product's use phase. These emissions may originate from various sources, such as nuclear, oil, coal, natural gas, wind, or solar energy. For these specific expenditures, we use an emission converter process that transforms expenditures into energy quantities (kWh, kg, and ℓ) and then into CO_2e emissions. While price estimates for energetic products are extracted from annual statistics of the SDES, the *Agence de la transition écologique* (the French Agency for Ecological Transition, ADEME) provides the emission structure of energetic products in the Base carbon V23.0. We establish an emissions converter table (Table 1) from these data to convert expenditures into CO_2e emissions.

Data on household vehicles allow us to connect each type of vehicle to its respective fuel type, including gasoline, diesel, liquefied petroleum gas, or electricity. Similarly, differentiating home energy sources enables matching with varying emissions intensities. However, a challenge arises from the combined energy

6. *Purchaser price is the amount of money paid by the final purchaser for the good or service produced, including taxes, subsidies, and margins.*
7. *The concordance matrix is available in the supplementary materials of Ivanova* et al. *(2017).*
8. *Expenditures related to direct emissions are excluded.*

Table 1 – **Emissions converter for the main energetic sources in 2017**

Consumption item	Energy source	Consumption price structure				Emission structure			
		Unit	HTT(1)	HTVA(2)	TTC(3)	Unit	Combustion	Upstream	Total
Transport	Gazole	€/ℓ	0.48	1.03	1.23	$kgCO_2e/ℓ$	2.51	0.655	3.165
	SP98	€/ℓ	0.54	1.2	1.44	$kgCO_2e/ℓ$	2.43	0.409	2.839
	SP95-E10	€/ℓ	0.49	1.13	1.35	$kgCO_2e/ℓ$	2.43	0.409	2.839
	SP95	€/ℓ	0.49	1.15	1.38	$kgCO_2e/ℓ$	2.43	0.409	2.839
	GPL	€/ℓ	0.53	0.62	0.74	$kgCO_2e/ℓ$	1.60	0.262	1.862
Energy	Electricity	€/kWh	0.11	0.14	0.16	$kgCO_2e/kWh$	0.04	0.016	0.057
	Natural gas	€/kWh	0.05	0.06	0.07	$kgCO_2e/kWh$	0.20	0.039	0.239
	Domestic fuel oil	€/ℓ	0.50	0.62	0.74	$kgCO_2e/ℓ$	2.68	0.571	3.251
	Propane	€/kWh	0.11	0.11	0.13	$kgCO_2e/kWh$	0.23	0.027	0.257
	Butane	€/kg	2.03	2.03	2.44	$kgCO_2e/kg$	2.95	0.487	3.437
	Coal	€/kg	-	0.15	-	$kgCO_2e/kg$	2.49	0.230	2.720
	Wood	€/kg	-	-	6.53	$kgCO_2e/kg$	0.01	0.016	0.030

(1) HTT (*hors toutes taxes)* excludes taxes.(2) HTVA (*hors taxe sur la valeur ajoutée*) adds to HTT the national tax on energetic products.
(3) TTC (*toutes taxes comprises*) encompasses the French value-added tax.
Note: Natural gas and propane are expressed in kWh LCV (low calorific value).
Lecture: In 2017, one liter of gazole costs €1.23 TTC and emits around 3.165 kg of CO_2e.
Field: Metropolitan France.
Source: SDES 2022, ADEME, *Base carbone* V23.0.

bill expenditures that include both gas and electricity. Following Pottier *et al.* (2020), we approximate the split between these energy sources by allocating expenditures based on the proportion spent on electricity and gas (which are distinguishable) within a group of households sharing the same heating system characteristics.

The direct segment of the carbon footprint is calculated through a straightforward process. First, expenses are divided by the average energy price (in €/kWh, €/kg, €/ℓ). Then, they are multiplied by the emission factor (in kg of CO_2e per kWh, kg, or ℓ). As a result, for a household h, direct emissions E_h^{dir} are defined by:

$$E_h^{dir} = \sum_r \left[\frac{m_{h,r}}{p_r} \cdot v_r \right]$$

where p_r is the price[9] of the energy source r per quantity, $m_{h,r}$ is the expenditure of household h for the energy source r, and v_r is the emissions factor[10] for the energy source r.

Finally, the carbon footprint of the household h is defined as the sum of direct and indirect emissions stemming from consumption:

$$E_h^{tot} = E_h^{dir} + E_h^{ind}.$$

1.3. The Unequal Distribution of Emissions Across Households

1.3.1. Through the Vertical Dimension

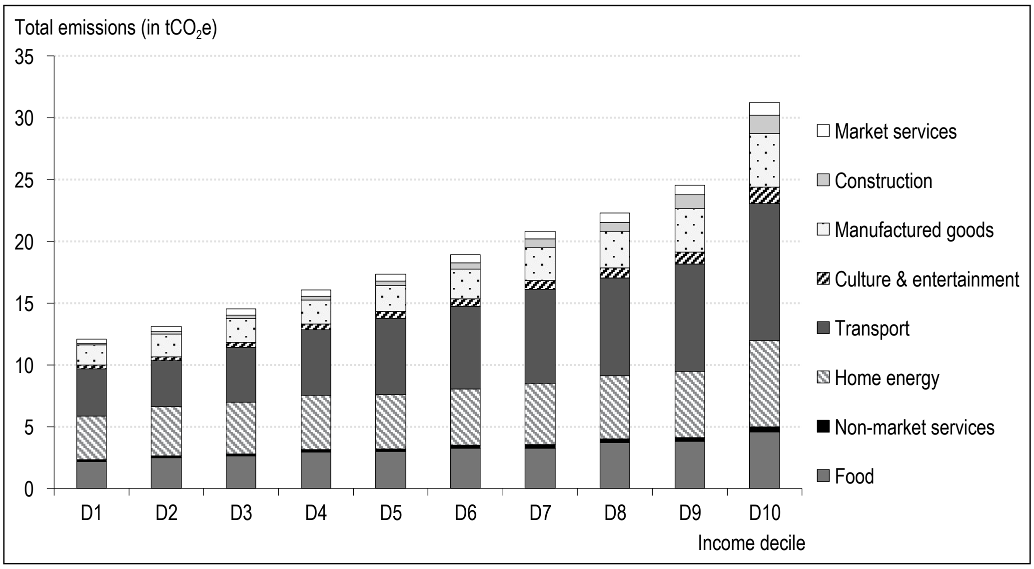
According to our calculation, on average, a French household emits 19 tons of CO_2e annually, and the median annual carbon footprint equals 16.5 tons of CO_2e. Overall, our estimations are close to those of Pottier *et al.* (2020) and Malliet (2020) for 2011, once the differences in scope are taken into account. Indeed, unlike them, we do not include emissions stemming from public administration[11] in our calculations. Furthermore, discrepancies can be explained by differences in methodology for estimating direct emissions, particularly including travel information from EMP.

Unsurprisingly, transport emerges as the largest contributor to the carbon footprint, averaging 6.5 tons of CO_2e. Home energy usage also represents a significant portion, emitting around 4.7 tons of CO_2e on average. Food consumption is the third most emitting category, with an average carbon footprint of 3.1 tons of CO_2e. These three sources accounted for over 75% of the average carbon footprint in 2017.

Figure I represents the carbon footprint of households segmented by consumption items for each income decile. The income is the income per consumption unit.[12]

9. We use purchaser prices, including taxes and margins.
10. The total emission structure includes upstream and combustion emissions.
11. While Pottier et al. *(2020) found that these emissions represent an additional 2.5 tCO_2e in the annual carbon footprint of French households, Malliet (2020) suggested that this could represent more than 3.5 tCO_2e. After this correction, our results are very close: an average of 21 tCO_2e corrected for Malliet (2020) and an average of 19 tCO_2e corrected for Pottier* et al. *(2020).*
12. It is derived from the disposable income adjusted for household composition using the modified OECD equivalence scale. This scale assigns a weight of 1 to the first adult, 0.5 to the second adult and subsequent individuals aged 14 and above, and 0.3 to each child under 14.

Figure I – **Average carbon footprint by income decile**



Note: On average, households belonging to the highest income decile (D10) emit 31 tons of CO_2e per year.
Field: Metropolitan France (12,081 observations).
Source : INSEE, *Enquête Budget de Famille* 2017, SDES, *Enquête Mobilité des Personnes* 2019, Exiobase 3.

On average, households in the top 10% of the income distribution emit 31 tons of CO_2e. This represents 2.6 times the carbon footprint of households in the bottom 10%, which emit, on average, 12 tons of CO_2e. As Pottier *et al.* (2020) emphasized, at least three effects might explain households' carbon footprint distribution. Firstly, the "volume effect" reflects the linear dependency between expenditures and emissions. This effect is linked to the methodology used to compute the carbon footprint. Indeed, since expenditures are multiplied by carbon intensities, an increase in expenditures results in a rising level of emissions, all else being equal (Pottier *et al.,* 2020). However, the ratio of annual expenditures between the first and the last decile is approximately 3.2, slightly higher than the emissions ratio.[13] This refers to the second effect, known as the "structure effect" which reflects that consumption patterns tend to vary as income grows. This argument explains why the carbon intensity of consumption of low-income households is generally higher than that of high-income households (Lenglart *et al.*, 2010; Pottier *et al.*, 2020). The carbon intensity of consumption amounts to 0.85 kgCO_2e per euro spent for low-income households, compared to 0.66 for high-income households. This suggests that certain emission categories may reach a saturation threshold as income increases. Once essential needs such as energy and food are met, high-income households can reallocate their spending towards products with lower carbon intensity (Weber & Matthews, 2008; Büchs & Schnepf, 2013). It is the third effect, known as the "quality effect", which suggests that there might be imbalances between expenditures and emissions attributable to product quality. Higher expenditures generally indicate the purchase of higher-quality products, which often have a relatively lower carbon footprint compared to cheaper alternatives. In our study, consumption is aggregated and linked to the carbon intensity of an average product. Therefore, we cannot account for this quality effect, potentially leading to overestimating the carbon footprint for high-income households.

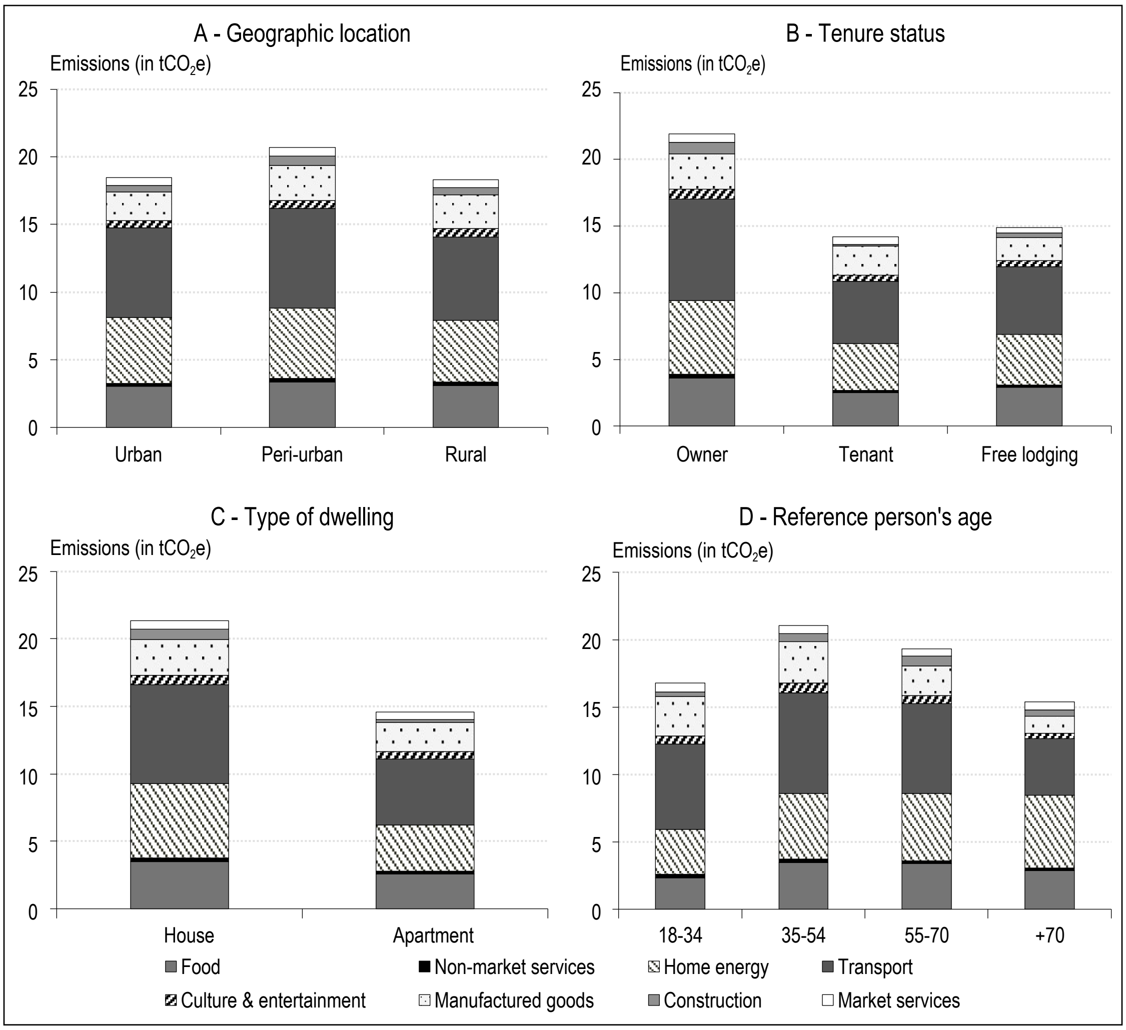
1.3.2. Through the Horizontal Dimension

While the analysis by income level provides insight into the distribution of household carbon footprints, an analysis by socioeconomic variables is also crucial. Figure II shows that the carbon footprint and its decomposition by types of consumption varies with socioeconomic characteristics.

The carbon footprint structure is, on average, close in rural and urban areas (Figure II-A). Peri-urban households typically emit more than rural and urban households due to mobility needs. However, rural households exhibit significantly higher variance in emissions,[14] nearly double that of urban households, meaning that rural households' carbon footprints are more

13. Notice also that the income ratio between D1 and D10 (around 6.2) is even higher than the consumption ratio. This confirms that the level of consumption decreases and the fraction of savings increases as income grows.
14. Households in rural areas exhibit a carbon footprint variance of 172.05, whereas those in urban areas have a variance of 96.34.

Figure II – **Carbon footprint by socioeconomic characteristic**



Note: On average, households living in apartments emit less than 15 tons of CO_2e.
Field: Metropolitan France (12,081 observations).
Source: INSEE, *Enquête Budget de Famille 2017*, SDES, *Enquête Mobilité des Personnes 2019*, Exiobase 3.

varied than those in cities and suburbs (Pottier *et al.*, 2020). Regarding the tenure status of the residence (Figure II-B), owners have a carbon footprint 55% higher than tenants, primarily due to higher construction, energy and transportation expenditures. If it is intuitive that construction and energy expenditures vary with tenure status, differences in transportation expenditures regarding tenure status pose interpretative challenges. The main difference between households living in houses versus apartments arises from construction and energy use (Figure II-C). There is a concave relationship between the age of the reference person and emissions level (Figure II-D). Changes in transportation habits primarily drive fluctuations in carbon footprint over a lifetime, which tends to first increase with age and then sharply decrease, by around one third between 35-54 and more than 70. This decrease is not offset by an increase in home energy emissions, which increases by only 10%, despite being 60% higher for 55 years old and more than for relatively younger households. Interestingly, the slight difference between the 35-54 and 55-70 age cohorts is primarily due to lower purchases of manufactured goods.

Additionally, in the Online Appendix (see Figure S1-I), we display the average household carbon footprint by education level and home energy source. The education level is typically a proxy for income, though there is significant variation in emissions among higher education levels. Regarding home energy use, households using electricity for heating have the lowest emissions, approximately 20% lower than average households. However, despite having low home energy emissions, households heating with renewable sources counterbalance this advantage with a significant carbon footprint from transportation.

2. Understanding Factors Influencing Households' Carbon Footprint

2.1. The Main Determinants of the Household Carbon Footprint

To identify the most relevant determinants of the carbon footprint of French households, we rely on the extensive literature available. Firstly, we acknowledge the role of income in leading the analysis of households' carbon footprint (Weber & Matthews, 2008; Büchs & Schnepf, 2013) due to the interlink between income and expenditures and the methodological approach used to compute household emissions (Pottier *et al.*, 2020). Socioeconomic variables such as household size and composition are crucial in this analysis (Gough *et al.*, 2011; Büchs & Schnepf, 2013). These characteristics may reflect divergent needs and consumption behaviours, influenced further by the age of the reference person and her education level (Lenglart *et al.*, 2010; Bourgeois *et al.*, 2021). If socioeconomic characteristics may explain differences in emissions levels, households' carbon footprint also depends on individual choices, more or less constrained, which directly influence their emissions level, especially that of direct emissions. For instance, home energy source (Reinders *et al.*, 2003; Wiedenhofer *et al.*, 2013; Pottier *et al.*, 2020), dwelling type (Nässén, 2014; Malliet, 2020), tenure status (Charlier, 2015; Bourgeois *et al.*, 2021), geographic location (Herendeen *et al.*, 1981; Duarte *et al.*, 2012; Gill & Moeller, 2018) or car dependency (Bureau, 2011; Wiedenhofer *et al.*, 2013) can reflect these behavioural patterns.

Consistent with the literature and the previous empirical results, our econometric model includes variables that encompass all these dimensions and therefore takes into account the influence of both socioeconomic characterisics and household decisions. We include household size, the reference person's age (four age groups), and her education level[15] (four levels, based on the International Standard Classification of Education – ISCED). The variables related to individual choices include the type of urban unit, the number of fossil fuel vehicles owned, the home energy source,[16] the dwelling type (i.e., house or apartment), and the tenure status (i.e., owner, tenant or free lodging). The type of urban unit reflects the influence of mobility needs on carbon footprints, particularly in isolated regions where car dependency is high (Orfeuil, 2020). It is based on urban area zoning,[17] categorized into three groups: urban (reference group), rural, and peri-urban areas.[18] Descriptive statistics are available in the Online Appendix (see Table S1-2).

2.2. OLS and Quantile Regression Models

We use two approaches to assess the relative importance of each set of variables on carbon emissions. The first one consists in implementing multivariate nested models within the OLS framework. Model (1) includes only socioeconomic variables X_1. Then, model (2) is augmented with income dummies K_d to test whether the socioeconomic variables are still relevant for explaining the logarithm of the carbon footprint E^S of type S (i.e., total, direct, or indirect). Finally, we add a set of variables X_3 related to consumption choices and form model (3):

$$\ln\left(E^S\right) = \alpha + \beta_1 X_1 + \sum_{d=1}^{9} \beta_{2,d} K_d + \beta_3 X_3 + \varepsilon$$

where α is a constant, and ε an error term. For each specification, we provide statistics such as the variance inflation factor (VIF) to monitor the risk of multicollinearity, as well as the AIC and BIC criteria to aid in model selection. Finally, standard errors are estimated using heteroscedasticity-consistent covariance matrix estimators.

In the second approach, we use quantile regressions to capture the impact of household characteristics on different quantiles of emissions levels. Unlike the OLS framework, which estimates the conditional mean, quantile regression estimates the conditional quantiles of a response variable given a set of predictors. This approach, introduced by Koenker & Bassett (1978), enables us to explore how relationships vary across different quantiles of emissions.

The most comprehensive model is retained for quantile regressions. We assume that the conditional quantiles of the carbon footprints distribution have a linear form:

$$\mathfrak{Q}_\tau\left(\ln\left(E^S\right)|X\right) = X'\beta_\tau$$

where τ corresponds to the different quantiles, and X is the set of predictors. We consider $\tau \in \{0.10; 0.25; 0.50; 0.75; 0.90\}$. Following Koenker

15. The first level (reference) comprises households with no educational background (i.e. no diploma or basic education). The second level is upper secondary education (e.g., A-level diploma or professional certification). The third level considers the first tertiary degree of education (e.g., short-cycle tertiary education or Bachelor's). The fourth level includes a second tertiary education degree (e.g., master's degrees, engineering, or doctorate).

16. Categorized as follows: oil and coal (reference group), electricity, gas, renewables (i.e. wood, solar, aerothermal, and geothermal), and others.

17. https://www.insee.fr/fr/statistiques/1281191

18. For urban households, we consider households living in towns belonging to major, medium, and minor centers. For households living in peri-urban, we consider the towns belonging to the suburbs of a major center and multipolarized towns in large urban areas. For rural households, we consider households living in isolated towns, towns included in suburbs of medium and small centers, and other multipolarized towns.

& Bassett (1978), for each τ, β_τ is estimated by solving the following minimization problem:

$$\widehat{\beta}_\tau = \arg\min_\beta \frac{1}{N}\sum_{w=1}^{N}\rho_\tau\left[\ln\left(E_w^s\right) - X_w^{'}\beta\right]$$

where w is a household and $\rho_\tau(.)$ a test function defined by:

$$\rho_\tau(u)\begin{cases}\tau u & \text{for } u \geq 0\\ (\tau-1)u & \text{for } u < 0\end{cases}$$

The estimator of a quantile regression is the least absolute deviation estimator. We use a bootstrapping approach with 1,000 replications to estimate standard errors.

3. Econometric Results

3.1. The OLS Framework

3.1.1. The Average Impact of Factors on Total Emissions

Let us begin by looking at the relationships between household characteristics, household decisions, and the carbon footprint through nested models. In model (1a) (Table 2), we estimate the impact of household characteristics on total emissions. Initially, we assess whether these variables are helpful in explaining household carbon footprint without taking income into account.

We observe a positive relationship between the household size and total emissions. At a given age and education level of the reference person, an additional individual in the household generates a carbon footprint 22% higher on average. The household's carbon footprint also varies with its position within the age pyramid. Lenglart *et al.* (2010) show that compared to a household with a reference person aged over 59, a relatively younger household exhibits different consumption patterns and, consequently, distinct carbon emissions. Our results show that compared to households whose reference person is between 18 and 34 years old, households with a reference person aged 55-70 emit significantly more. Given the size of the

Table 2 – **OLS regression results for total emissions**

		(1a)	(2a)	(3a)
Constant		1.748*** (0.022)	1.735*** (0.025)	1.885*** (0.029)
Number of individuals		0.218*** (0.005)	0.074*** (0.005)	0.047*** (0.004)
Reference person's age (*Ref.*: 18-34)	35-54	0.156*** (0.016)	0.100*** (0.014)	0.035*** (0.013)
	55-70	0.387*** (0.017)	0.194*** (0.015)	0.044*** (0.014)
	+71	0.312*** (0.020)	0.118*** (0.017)	−0.008 (0.017)
Reference person's education level (*Ref.*: no education)	Upper secondary	0.253*** (0.013)	0.128*** (0.012)	0.070*** (0.010)
	First tertiary	0.441*** (0.016)	0.166*** (0.014)	0.134*** (0.013)
	Second tertiary	0.587*** (0.019)	0.169*** (0.019)	0.194*** (0.017)
Tenure status (*Ref.*: owner)	Tenant			−0.110*** (0.011)
	Free lodging			−0.150*** (0.040)
Home energy source (*Ref.*: fuel and coal)	Electricity			−0.155*** (0.013)
	Gas			−0.090*** (0.013)
	Renewable			−0.221*** (0.014)
	Other			−0.218*** (0.036)
Type of dwelling (*Ref.*: apartment)	House			0.097*** (0.011)
Type of urban unit (*Ref.*: urban)	Peri-urban			−0.001 (0.013)
	Rural			0.016 (0.013)
Number of fossil fuel vehicles				0.230*** (0.007)
Income control		No	Yes	Yes
Observations		12,081	12,081	12,081
R^2		0.262	0.448	0.555
Variance Inflation Factor (max)		1.39	1.78	2.23
AIC		20,057.2	16,677.1	14,074.9
BIC		20,123.8	16,810.2	14,274.7

Note: Heteroscedastic-robust standard errors are in parentheses. ***, ** and * indicate a p-value of 1%, 5% and 10% respectively. The dependent variable is the logarithm of total emissions (in tCO_2e).
Lecture: In model (1a), one additional individual in the household increases the total carbon footprint by 22% on average.

household and the education level of the reference person, households with a reference person between 50 and 70 years old have an average carbon footprint 40% higher than those between 18 and 34. Finally, the higher the education level, the higher the carbon footprint (Baiocchi *et al.*, 2010; Lenglart *et al.*, 2010; Büchs & Schnepf, 2013). Accounting for age and size of the household, households with second tertiary level have a carbon footprint approximately 60% larger than those with no education.

Unsurprisingly, when income levels are incorporated into the analysis (model (2a)), the explanatory power increases by around 70%, suggesting the importance of this variable for analysing households' carbon footprints (Lenglart *et al.*, 2010; Pottier *et al.*, 2020; Douenne, 2020). Household size, the age and education level of the reference person remain statistically significant, but their importance is lesser. The coefficients' magnitude decreases by approximately 60% on average for previously statistically significant variables when income is included. For example, the difference in average carbon footprints between the most educated and least educated households narrows to less than 20%.

In model (3a), we examine if including household decisions modifies the previous results. We observe that the home energy source is also a determining factor of carbon footprint. Households using sources other than oil or coal unsurprisingly have a lower carbon footprint. Keeping other variables constant, households using renewable energy as their primary source have a carbon footprint 22% lower than households heating with oil or coal. However, it is important to stress that the energy source used in the dwelling is particularly linked to the type of dwelling (Malliet, 2020). While establishing a direct causal relationship between dwelling type and energy demand is complex, the findings indicate that households in apartments generally have a lower carbon footprint than households living in houses. For instance, in our sample, 65% of households living in apartments reside in relatively small buildings where natural gas is predominantly used as the main energy source. In contrast, house households are likelier to be homeowners,[19] which correlates with higher emission levels. Indeed, tenure status is crucial in understanding variations in household emissions. Holding other factors constant, households owner of their residence have higher emissions levels than the others.

Regarding mobility, the number of fossil fuel vehicles in the household is statistically significant. Controlling for other observed variables, an additional fossil fuel vehicle leads to a 23% increase in emissions. Conversely, the type of urban unit makes no significant differences in carbon emissions when other characteristics and income effects are controlled for. In other words, income and household characteristics emerge as critical factors in explaining carbon footprint variation across different types of urban units.

Additionally, we observe a sharp increase in the model's explanatory power when we add household decision variables, with the R^2 growing from 45% to more than 55%. This highlights the crucial role of decision variables in carbon footprint analysis. Assuming that the variable selection is optimal, household decisions increase the R^2 by 24%, compared to a model containing only socioeconomic variables and income.

Whether these relationships are confined to the analyzed emission source remains to be seen (Duarte *et al.*, 2012; Büchs & Schnepf, 2013). We should investigate whether certain characteristics or choices better explain direct emissions compared to indirect emissions and vice versa.

3.1.2. Direct and Indirect Emissions

This section compares the analysis of direct emissions (Table 3) and indirect emissions (Table 4). Based on models (1b), (2b), (1c), and (2c), we observe that the link of household size is stronger with indirect emissions than with direct emissions, whether controlling for income effects or not. As the household size increases, there might be economies of scale to achieve regarding direct emissions rather than indirect emissions (Lenglart *et al.*, 2010; Büchs & Schnepf, 2013). For instance, we may assume that the birth of a child will lead to additional expenditures in terms of textiles, food, or medical care rather than fuel consumption or home heating, for instance. We also observe a clear difference between direct and indirect emissions regarding the age of the reference person. The emission gap between age groups is statistically significant for almost all age groups when explaining direct emissions, whether controlling for income effects and other variables or not (models (2b) and (3b)). Contrary to what is generally established (Lenglart *et al.*, 2010; Büchs & Schnepf, 2013; Nässén, 2014), older households have, on average, higher direct emissions than younger households. For direct emissions, model (3b) suggests that the

19. *While 88% of house residents are owners (including owners with mortgage), only 66% of apartment residents are owners.*

gap between 70 years old or more and young reference persons (18-34) is larger than between 55-70 years old and young reference persons. However, this does not apply to indirect emissions, where the oldest households indirectly emit, on average, 10% less than youngest households when controlling for income and other variables (model (3c)).

There are similarities and differences in the impact of household decisions on direct and indirect emissions. Unsurprisingly, the type of energy used in the dwelling is statistically significant in explaining direct emissions (model (3b)), but makes no difference to indirect emissions. Moreover, living in a house rather than in an apartment is positively related to direct emissions and negatively related to indirect emissions. This difference likely arises because households living in houses have more space to heat, or do so more intensively due to different insulation levels, compared to those living in apartments. Transportation solutions to commute might also indirectly explain the relationship.

Concerning the type of urban unit, contrary to expectations, rural households have lower direct emissions than urban households, while urban households have lower indirect emissions on average. The difference between peri-urban and urban areas is not significant. A higher number of fossil fuel vehicles in a household is significantly and positively linked to higher direct and indirect emissions. As for the positive and significant relationship between the number of fossil fuel vehicles in households and indirect emissions, this could be due to the fact that an additional car entails expenditure on servicing and maintenance, which is likely to increase indirect emissions.

The comparison of the three models (i.e., a, b, and c) suggests that the explanatory power of the models distinguishing between emission sources is lower than those focusing on the total carbon footprint. Then if we were to rank the groups

Table 3 – **OLS regression results for direct emissions**

		(1b)	(2b)	(3b)
Constant		0.856*** (0.031)	0.814*** (0.037)	0.999*** (0.039)
Number of individuals		0.212*** (0.007)	0.071*** (0.007)	0.017*** (0.006)
Reference person's age (*Ref.:* 18-34)	35-54	0.248*** (0.023)	0.200*** (0.021)	0.083*** (0.018)
	55-70	0.535*** (0.024)	0.354*** (0.023)	0.077*** (0.020)
	+71	0.526*** (0.028)	0.342*** (0.027)	0.110*** (0.024)
Reference person's education level (*Ref.:* no education)	Upper secondary	0.282*** (0.018)	0.156*** (0.017)	0.052*** (0.014)
	First tertiary	0.372*** (0.022)	0.105*** (0.021)	0.065*** (0.017)
	Second tertiary	0.405*** (0.026)	0.013 (0.026)	0.091*** (0.021)
Tenure status (*Ref.:* owner)	Tenant			−0.093*** (0.015)
	Free lodging			−0.165*** (0.055)
Home energy source (*Ref.:* fuel and coal)	Electricity			−0.275*** (0.017)
	Gas			−0.132*** (0.017)
	Renewable			−0.404*** (0.018)
	Other			−0.359*** (0.045)
Type of dwelling (*Ref.:* apartment)	House			0.334*** (0.015)
Type of urban unit (*Ref.:* urban)	Peri-urban			−0.007 (0.016)
	Rural			−0.044*** (0.016)
Number of fossil fuel vehicles				0.396*** (0.010)
Income control		No	Yes	Yes
Observations		12,026	12,026	12,026
R^2		0.146	0.256	0.498
Adjusted R^2		0.146	0.255	0.498
Variance Inflation Factor (max)		1.40	1.77	2.22
AIC		27,343.8	25,710.2	20,981.4
BIC		27,410.3	25,843.3	21,181.1

Note: Heteroscedastic-robust standard errors are in parentheses. ***, ** and *, indicate a p-value of 1%, 5% and 10% respectively.
The dependent variable is the logarithm of direct emissions (in tCO_2e).
Lecture: In model (1b), one additional individual in the household increases direct emissions by 21% on average.

Table 4 – **OLS regression results for indirect emissions**

		(1c)	(2c)	(3c)
Constant		0.979*** (0.026)	0.989*** (0.029)	0.984*** (0.040)
Number of individuals		0.248*** (0.006)	0.089*** (0.006)	0.081*** (0.006)
Reference person's age (*Ref.:* 18-34)	35-54	0.077*** (0.019)	0.015 (0.017)	−0.001 (0.017)
	55-70	0.291*** (0.021)	0.077*** (0.019)	0.036* (0.019)
	+71	0.137*** (0.024)	−0.075*** (0.021)	−0.091*** (0.022)
Reference person's education level (*Ref.:* no education)	Upper secondary	0.267*** (0.016)	0.132*** (0.015)	0.102*** (0.015)
	First tertiary	0.552*** (0.019)	0.249*** (0.018)	0.221*** (0.018)
	Second tertiary	0.758*** (0.023)	0.291*** (0.024)	0.279*** (0.023)
Tenure status (*Ref.:* owner)	Tenant			−0.100*** (0.015)
	Free lodging			−0.085* (0.047)
Home energy source (*Ref.:* fuel and coal)	Electricity			0.013 (0.019)
	Gas			0.021 (0.019)
	Renewable			0.008 (0.020)
	Other			−0.007 (0.043)
Type of dwelling (*Ref.:* apartment)	House			−0.085*** (0.015)
Type of urban unit (*Ref.:* urban)	Peri-urban			0.013 (0.020)
	Rural			0.075*** (0.019)
Number of fossil fuel vehicles				0.138*** (0.008)
Income control		No	Yes	Yes
Observations		12,081	12,081	12,081
R^2		0.262	0.408	0.424
Adjusted R^2		0.262	0.405	0.423
Variance Inflation Factor (max)		1.39	1.78	2.23
AIC		25,081.8	22,476.1	22,125.6
BIC		25,148.4	22,609.3	22,325.3

Note: Heteroscedastic-robust standard errors are in parentheses. ***, ** and *, indicate a p-value of 1%, 5% and 10% respectively.
The dependent variable is the logarithm of indirect emissions (in tCO_2e).
Lecture: In model (1c), one additional individual in the household increases indirect emissions by 25% on average.

of variables by relevance according to emission sources, we would say that decision variables are relatively better than socioeconomic characteristics in explaining direct emissions. Indeed, the R^2 value nearly doubled between models (2b) and (3b), a result closely tied to the methodology used to estimate direct emissions. In contrast, the decision variables introduced in model (3c) only marginally enhance the explanatory power. On the contrary, socioeconomic variables could be more effective in expliaing indirect emissions than direct emissions (R^2 is higher in model (1c) than in model (1b)).

While these multivariate models offer valuable insights to enlighten relationships between different groups of variables and discerning their relevance in explaining the two types of carbon emissions, they only explore relations to the average. Indeed, some relationships may disappear or be amplified when considering other quantiles of the distribution of carbon footprints. Therefore, it is interesting to identify relationships within a more flexible analytical framework.

3.2. The Quantile Regression Framework

3.2.1. The Impact of Income Across Different Emission Quantiles

Before analyzing the influence of household characteristics on their carbon footprint through quantile regressions, it is important to understand the impact of income on emissions. In this section, our goal is to estimate the elasticity of carbon footprint with respect to income using the most comprehensive model:

$$\ln\left(E^S\right) = \alpha + \beta_1 X_1 + \beta_2 \ln\left(X_2\right) + \beta_3 X_3 + \varepsilon$$

where X_2 is the household's disposable income. We also estimate the elasticity at various emissions quantiles through quantile regressions. In Figure III, we display the beta coefficients, along with their respective confidence intervals, reflecting the income elasticity of the carbon footprint at the mean and various quantiles. First, the income elasticity of carbon footprint is always below unity, confirming that the household carbon footprint grows less rapidly than income. Second, our OLS estimates are relatively small compared to other findings. While Lenglart *et al.* (2010) found an income elasticity of about 0.6, Chancel (2022) and Malliet (2020) found an estimate of 0.9 and 0.5, respectively. The divergence between our results and theirs is attributable to methodological differences, particularly the non-integration of other variables in the estimation (Lévay *et al.,* 2022).

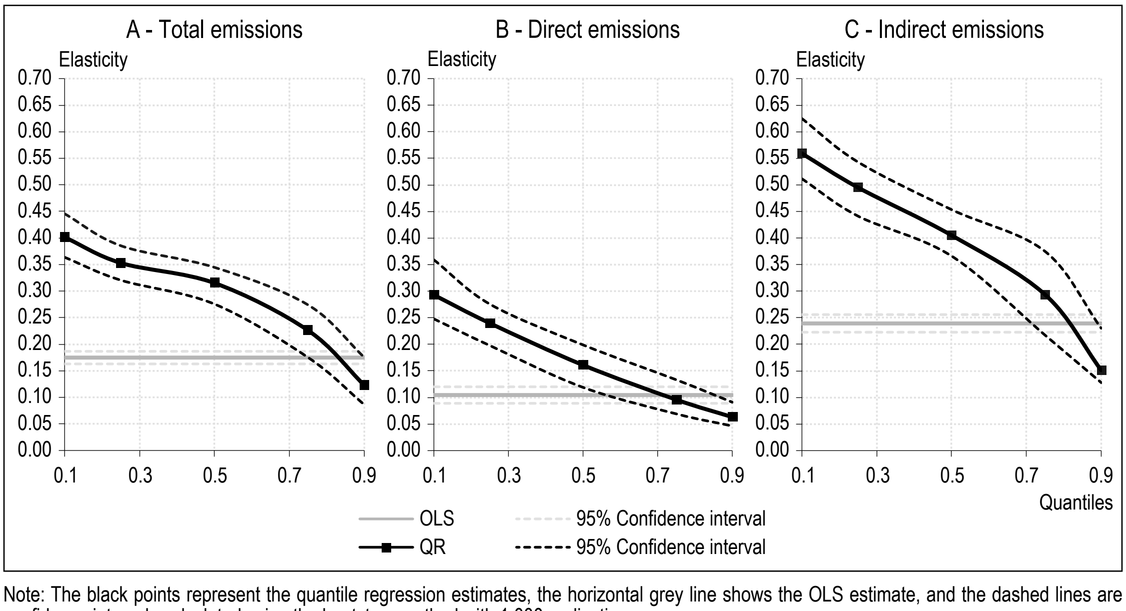
The quantile regression estimates highlight a significant variation in elasticity across different emissions levels, with income elasticity regarding total emissions ranging from 0.4 at the first decile to 0.1 at the last decile. This indicates that income differences have less impact at the top of the emissions distribution than at its bottom, emphasizing a relative decoupling between income and emissions as we move towards the top of the conditional distribution. The income elasticity is higher for indirect emissions than for direct ones. This means indirect emissions are more responsive to income changes across all quantiles than direct emissions (Figure III-C). Additionally, income variations have minimal impact at the upper end of the distribution, as evidenced by the small income elasticity of direct emissions (Figure III-B) for this group.

3.2.2. The Impact of Socioeconomic Factors on Various Emission Quantiles

As in the most comprehensive models of the analysis presented in section 3.1, the following quantile regressions include income deciles and the whole set of variables (demographic characteristics and household decision variables). As a result, these estimates can be directly compared to findings of section 3.1.

Model (4a) considers the logarithm of total carbon emissions as the dependent variable (Table 5). Regarding household size, we observe a positive relationship with total emissions whatever the quantile considered. Holding all other variables constant, an additional household member is associated with a 5% increase in the first decile of the conditional carbon footprint distribution, compared to a 4% increase in the last decile. The effect of household size is more or less the same as that obtained with the OLS model (see model (3a)). The age of the household reference person does not have the same impact on the different quantiles of the distribution of total household emissions. Middle-aged (35-54) and older adults (55-70) tend to have slightly higher carbon footprints than younger adults (18-34), except for higher deciles, suggesting that age differences are less pronounced at very high emission levels, possibly due to consistently high consumption patterns across age groups.

Figure III – **The income elasticity of household carbon footprint at the mean and at various quantiles**



Note: The black points represent the quantile regression estimates, the horizontal grey line shows the OLS estimate, and the dashed lines are confidence intervals calculated using the bootstrap method with 1,000 replications.
Lecture: For the quantile regression, conditional to the first decile, a 1% increase in the household's disposable income increases total emissions by 0.4%.

Table 5 – **Quantile regression results for total emissions**

		(4a)									
		0.10		0.25		0.50		0.75		0.90	
Constant		1.168***	(0.059)	1.534***	(0.042)	1.949***	(0.037)	2.254***	(0.036)	2.678***	(0.060)
Number of individuals		0.050***	(0.006)	0.045***	(0.005)	0.041***	(0.004)	0.044***	(0.005)	0.042***	(0.008)
Reference person's age (*Ref.:* 18-34)	35-54	0.057***	(0.023)	0.042***	(0.016)	0.033**	(0.014)	0.041**	(0.016)	0.009	(0.023)
	55-70	0.056*	(0.028)	0.039**	(0.017)	0.037**	(0.015)	0.040**	(0.019)	0.043	(0.028)
	+71	0.018	(0.034)	0.010	(0.019)	−0.004	(0.018)	−0.015	(0.022)	−0.067**	(0.027)
Reference person's education level (*Ref.:* no education)	Upper secondary	0.078***	(0.023)	0.081***	(0.013)	0.066***	(0.012)	0.048***	(0.015)	0.034*	(0.018)
	First tertiary	0.132***	(0.024)	0.143***	(0.016)	0.138***	(0.014)	0.113***	(0.015)	0.086***	(0.022)
	Second tertiary	0.186***	(0.030)	0.184***	(0.020)	0.157***	(0.020)	0.174***	(0.019)	0.216***	(0.032)
Tenure status (*Ref.:* owner)	Tenant	−0.122***	(0.023)	−0.088***	(0.013)	−0.086***	(0.013)	−0.098***	(0.012)	−0.130***	(0.018)
	Free lodging	−0.306***	(0.054)	−0.220***	(0.053)	−0.109**	(0.043)	−0.083***	(0.031)	−0.002	(0.058)
Home energy source (*Ref.:* fuel and coal)	Electricity	−0.160***	(0.025)	−0.155***	(0.016)	−0.161***	(0.015)	−0.157***	(0.016)	−0.142***	(0.022)
	Gas	−0.065***	(0.023)	−0.076***	(0.016)	−0.099***	(0.015)	−0.111***	(0.016)	−0.115***	(0.023)
	Renewable	−0.257***	(0.027)	−0.230***	(0.016)	−0.222***	(0.016)	−0.199***	(0.016)	−0.179***	(0.022)
	Other	−0.344***	(0.056)	−0.262***	(0.045)	−0.184***	(0.039)	−0.144***	(0.034)	−0.088	(0.060)
Type of dwelling (*Ref.:* apartment)	House	0.151***	(0.022)	0.127***	(0.013)	0.103***	(0.013)	0.071***	(0.012)	0.035**	(0.019)
Type of urban unit (*Ref.:* urban)	Peri-urban	−0.040	(0.026)	−0.020	0.015)	0.009	(0.016)	0.023	(0.016)	0.029	(0.022)
	Rural	−0.020	(0.026)	0.001	0.015)	0.003	(0.016)	0.036*	(0.016)	0.035	(0.022)
Number of fossil fuel vehicles		0.237***	(0.010)	0.238***	(0.007)	0.214***	(0.007)	0.209***	(0.008)	0.182***	(0.013)
Income control		Yes									
Observations		12,081									

Note: Standard errors are in parentheses, computed using a bootstrapping approach with 1,000 replications. ***, ** and *, indicate a p-value of 1%, 5% and 10% respectively.
Lecture: Conditional to the first decile of the total emissions distribution, an additional individual in the household generates an increase of 5% in emissions.

However, when turning to direct emissions (see model (4b), Table 6), the gap between households with reference person aged 71 years or over and those with reference person aged 18-34 is significant for emissions at or below the median, with the strongest effect in the first quartile. By contrast, the gap between the two age groups is of opposite sign for indirect emissions (see model (4c), Table 7), but is only significant at the upper end of the conditional distribution. This suggests that in the lowest emission segment, elderly households may have higher energy needs than younger ones. However, at higher emission levels, older households might consume less food or market services compared to younger households (see Figure II).

For education level, we find a similar relationship as in OLS models. The emission gap between households with second tertiary education and no education is quite large at all quantiles of the distribution. The gap is even greater between households with tertiary education and those with no education.

3.2.3. The Impact of Consumption Choices at Different Emission Quantiles

We find significant relationships between carbon emissions and consumption choices variables with our quantile regressions, as for the OLS estimations. Regarding tenure status, we again find a higher carbon footprint among homeowners than renters. It is interesting to note that the difference between homeowners and renters tends to increase as we move up the conditional distribution of indirect emissions but decreases in the case of direct emissions. For low emitters, the difference in direct emissions is larger between homeowners and renters, with homeowners emitting more due to higher home energy expenditures. However, the gap between homeowners and renters is more pronounced at the upper quantile of the distribution for indirect emissions.

Beyond the fact that households using oil or coal for heating consistently have higher carbon footprints, the largest emission gaps are observed with renewables, or any other sources besides

Table 6 – **Quantile regression results for direct emissions**

		(4b)									
		0.10		0.25		0.50		0.75		0.90	
Constant		−0.097	(0.074)	0.575***	(0.049)	1.196***	(0.039)	1.686***	(0.043)	2.063***	(0.047)
Number of individuals		0.011	(0.011)	0.017**	(0.007)	0.010*	(0.006)	0.009*	(0.005)	0.009	(0.008)
Reference person's age (*Ref.:* 18-34)	35-54	0.097**	(0.038)	0.082***	(0.022)	0.067***	(0.018)	0.046***	(0.016)	0.054***	(0.022)
	55-70	0.078*	(0.040)	0.075***	(0.024)	0.059***	(0.021)	0.058***	(0.018)	0.055***	(0.021)
	+71	0.105**	(0.044)	0.110***	(0.028)	0.086***	(0.024)	0.085***	(0.020)	0.082***	(0.025)
Reference person's education level (*Ref.:* no education)	Upper secondary	0.074***	(0.027)	0.047***	(0.019)	0.050***	(0.014)	0.055***	(0.014)	0.051***	(0.017)
	First tertiary	0.073**	(0.034)	0.046**	(0.022)	0.067***	(0.018)	0.077***	(0.016)	0.054***	(0.019)
	Second tertiary	0.094**	(0.048)	0.086***	(0.028)	0.082***	(0.021)	0.105***	(0.021)	0.135***	(0.025)
Tenure status (*Ref.:* owner)	Tenant	−0.123***	(0.028)	−0.086***	(0.019)	−0.074***	(0.013)	−0.064***	(0.014)	−0.067***	(0.016)
	Free lodging	−0.569***	(0.146)	−0.175*	(0.082)	−0.102*	(0.053)	−0.050	(0.048)	−0.055	(0.051)
Home energy source (*Ref.:* fuel and coal)	Electricity	−0.266***	(0.026)	−0.277***	(0.021)	−0.281***	(0.015)	−0.281***	(0.018)	−0.293***	(0.019)
	Gas	−0.110***	(0.024)	−0.103***	(0.019)	−0.137***	(0.015)	−0.172***	(0.019)	−0.210***	(0.017)
	Renewable	−0.436***	(0.031)	−0.408***	(0.021)	−0.400***	(0.017)	−0.368***	(0.018)	−0.362***	(0.022)
	Other	−0.418***	(0.091)	−0.453***	(0.072)	−0.418***	(0.058)	−0.284***	(0.052)	−0.282***	(0.043)
Type of dwelling (*Ref.:* apartment)	House	0.667***	(0.041)	0.445***	(0.025)	0.285***	(0.016)	0.215***	(0.014)	0.149***	(0.016)
Type of urban unit (*Ref.:* urban)	Peri-urban	−0.003	(0.032)	−0.005	(0.018)	−0.003	(0.018)	0.008	(0.017)	0.005	(0.019)
	Rural	−0.049	(0.032)	−0.047**	(0.018)	−0.043**	(0.019)	−0.024*	(0.017)	0.010	(0.021)
Number of fossil fuel vehicles		0.366***	(0.012)	0.351***	(0.013)	0.340***	(0.008)	0.292***	(0.010)	0.258***	(0.010)
Income control		Yes									
Observations		12,026									

Note: Standard errors are in parentheses, computed using a bootstrapping approach with 1,000 replications. ***, ** and *, indicate a p-value of 1%, 5% and 10% respectively.
Lecture: Conditional to the first decile of the direct emissions distribution, an additional vehicle in the household generates an increase of 37% of emissions.

electricity or gas, particularly at the lower quantiles of the conditional distribution (cf. Tables 5 and 6). This suggests that transitioning from a highly carbon-intensive energy source to a less carbon-intensive one reduces in larger proportions the carbon footprint of current low emitters.

Concerning the type of dwelling, the difference in carbon footprints between households in houses and apartments decreases as we move up the conditional distribution. Controlling for the other characteristics, living in a house rather than an apartment increases the ninth decile of the conditional distribution of carbon footprints by only 15%, but increases the first decile by a much greater proportion of nearly 70%. This gap may stem from differences in energy needs for heating.

There is no significant differences in the conditional distribution of households total emissions with the type of urban unit once the other characteristics are taken into account. However, as in the OLS analysis, type of urban units differences, especially between urban and rural areas, appear statistically significant in explaining indirect emissions, and to a lesser extent, but in the opposite direction, direct emissions. The effect in the quantile regression framework tends to become more pronounced at both ends of the conditional distribution.

Finally, concerning the number of fossil fuel vehicles in the household, the impact appears to be larger at the lower end of the conditional distribution, regardless of the type of emissions considered. Having one additional fossil fuel vehicle car increases by around 40% more the first decile of direct emissions than the ninth one (0.366/0.258). This may be because low-consumption cars are typically more expensive, making them more accessible to affluent households. This could mitigate the carbon impact of an additional fossil fuel vehicle at high-emission segments. The frequency of car use could be important to consider as well. Finally, note that mean estimates are slightly higher than the impact of this variable on direct emissions at the middle of the distribution: all else being equal,

Table 7 – **Quantile regression results for indirect emissions**

		(4c)									
		0.10		0.25		0.50		0.75		0.90	
Constant		−0.026	(0.071)	0.514***	(0.057)	0.994***	(0.041)	1.504***	(0.051)	1.926***	(0.068)
Number of individuals		0.080***	(0.010)	0.080***	(0.007)	0.088***	(0.005)	0.063***	(0.008)	0.063***	(0.011)
Reference person's age (*Ref.:* 18-34)	35-54	0.034	(0.030)	0.025	(0.021)	0.001	(0.018)	0.006	(0.022)	−0.017	(0.033)
	55-70	0.068*	(0.039)	0.066**	(0.026)	0.052**	(0.020)	0.025	(0.026)	0.003	(0.038)
	+71	−0.010	(0.042)	−0.040	(0.028)	−0.062**	(0.026)	−0.110***	(0.027)	−0.185***	(0.040)
Reference person's education level (*Ref.:* no education)	Upper secondary	0.131***	(0.031)	0.132***	(0.020)	0.116***	(0.017)	0.066***	(0.017)	0.047*	(0.027)
	First tertiary	0.244***	(0.037)	0.259***	(0.023)	0.223***	(0.021)	0.178***	(0.021)	0.164***	(0.031)
	Second tertiary	0.315***	(0.041)	0.293***	(0.032)	0.249***	(0.024)	0.209***	(0.026)	0.282***	(0.048)
Tenure status (*Ref.:* owner)	Tenant	−0.040	(0.025)	−0.066***	(0.020)	−0.093***	(0.015)	−0.111***	(0.018)	−0.159***	(0.031)
	Free lodging	−0.133	(0.083)	−0.018	(0.062)	−0.026	(0.040)	−0.031	(0.044)	−0.124*	(0.077)
Home energy source (*Ref.:* fuel and coal)	Electricity	0.047	(0.040)	0.008	(0.029)	−0.008	(0.020)	−0.001	(0.026)	0.017	(0.028)
	Gas	0.087**	(0.039)	0.010	(0.027)	0.010	(0.020)	−0.004	(0.026)	0.011	(0.029)
	Renewable	0.078**	(0.042)	0.004	(0.032)	0.007	(0.021)	−0.009	(0.027)	0.008	(0.034)
	Other	0.003	(0.099)	−0.036	(0.050)	0.005	(0.044)	0.034	(0.046)	0.071	(0.092)
Type of dwelling (*Ref.:* apartment)	House	−0.150***	(0.026)	−0.076***	(0.019)	−0.061***	(0.016)	−0.049**	(0.018)	−0.036	(0.031)
Type of urban unit (*Ref.:* urban)	Peri-urban	0.007	(0.042)	0.005	(0.030)	0.020	(0.018)	0.048*	(0.025)	0.039	(0.033)
	Rural	0.097***	(0.037)	0.066**	(0.030)	0.057***	(0.017)	0.068***	(0.024)	0.076**	(0.031)
Number of fossil fuel vehicles		0.163***	(0.011)	0.136***	(0.012)	0.114***	(0.009)	0.118***	(0.010)	0.116***	(0.017)
Income control		Yes									
Observations		12,081									

Note: The standard errors are in parentheses, computed using a bootstrapping approach with 1,000 replications. ***, ** and *, indicate a p-value of 1%, 5% and 10% respectively.
Lecture: Conditional to the first decile of the total emissions distribution, an additional individual in the household generates an increase of 8% of emissions.

an additional fossil fuel vehicle increases direct emissions by about 40% on average, which is slightly higher than the impact conditional to the median carbon footprint (34% increase).

* *
*

In this study, we compute the carbon footprint of French households using an input-output model and data from the 2017 French Household Budget Survey. Our analysis reveals a wide disparity in carbon footprints among households. While income is recognized as a significant factor influencing carbon footprints (Weber & Matthews, 2008; Büchs & Schnepf, 2013; Pottier, 2022), substantial disparities within income groups suggest the existence of other sources of variation (Pottier *et al.*, 2020; Douenne, 2020). Hence, we explore whether these differences stem from socioeconomic characteristics such as the household size, the reference person's age and education level, or from household's decisions that directly influence emissions such as the tenure status, the home energy source, the type of dwelling, the type of urban unit and the number of fossil fuel vehicles owned by the household. We used multivariate nested models to unravel these relationships and evaluate if they remain constant across the emission distribution using quantile regressions.

Firstly, we showed that characteristics such as education level, household size, tenure status, or home energy source, remain significantly correlated with carbon footprints even after controlling for income differences. Therefore, these characteristics are of primary importance when estimating the repercussions of environmental policies. Secondly, we observed that other characteristics (and income) being equal, the type of urban unit (urban/peri-urban/rural) have a limited impact on carbon footprint variability and, consequently, on vulnerability to environmental policy. Thirdly, given the variables selected and the methodology, the group of household decision variables appears to explain a significant part of emissions variance, especially for direct emissions.

Considering the quantiles of the distribution rather than its mean confirms the variable importance of the household characteristics on direct as well as indirect emissions. Switching from a carbon‑intensive heating mode to a renewable one has more impact at the bottom of the distribution than at the top. Tenants tend to emit less than owners and the gap is larger at the top and bottom deciles than in the middle of the distribution. None of the relationships in the quantile regressions exhibit an inverse association across the segments of the conditional distribution studied. In other words, no variable shows a strictly divergent influence between the upper and lower segments of the distribution.

These findings could help French policymakers to build efficient and resilient strategies to curb GHG emissions while minimizing the welfare costs associated with the environmental transition. This study reveals that beyond income socioeconomic characteristics and household decisions are important to explain the carbon footprint distribution. Household decisons variables, which are also the most adjustable in the context of transition, appear to be the most important variables for understanding direct emissions, unlike socioeconomic characteristics, which are less or even not flexible, and therefore less likely to act as a lever for reducing their footprint. ☐

Link to the Online Appendix:
www.insee.fr/en/statistiques/fichier/8562082/ES545_Semet_OnlineAppendix.pdf

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