Greenhouse gas emissions of households food purchases in France: Does income matter?

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Abstract

This paper explores the theoretical inverted U-shape relationship between income level and environmental impact, namely the Environmental Kuznets Curve hypothesis, in the case of food consumption. The greenhouse gas emissions (GHGEs) associated with food purchases of French households were estimated and were compared between income classes.

Data on food purchases come from Kantar Worldpanel, a representative survey of French households. Our sample includes 8112 observations averaging 1998 to 2010 food-at-home purchases. Food groups were aggregated according to their nutritional characteristics and their animal or plant-based content. Using Life-Cycle-Analysis estimations from Greenext, the GHGEs associated with food-at-home purchases were expressed in g of CO2 equivalent per household (CO2eq). To allow comparisons even when purchases contained different amounts of energy, per calorie GHGEs were also estimated (in g CO2eq/2000 kcal) and were then regressed on income and age.

Total GHGEs associated with French household food-at-home purchases amount to 1.43 ton CO2eq per household per year and to 3.9kg eq per day. Both the amount of calories purchased for food-at-home per day and the GHGEs associated with those purchases were higher for lowest income households compared to richest households (+14.7%). However, GHGEs were lower for lowest income households when expressed per 2000 kcal (-9.6%). Once controlled by age, income disparities were still significant, though weaker. In richer households, the higher GHGEs per 2000 kcal purchased was associated with higher purchases for food groups with higher per-calorie GHGEs, such as cheese or fish. Hence, the results show that, for a given level of energy purchased, the environmental impact associated with food-at-home is increasing with increasing income. Consequently, in a public policy perspective, richer households should be the first target of diet change since their consumption is associated with higher GHGEs than lower income households.

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Introduction

The environmental impactof consumption is commonly associated with the stage of economic growth. In the environmental literature, the relationship between level of income per capita and environmental impact is assumed to show an inverted U-shape: this is the Environmental Kuznets Curve hypothesis, following the work of Grossman and Krueger (1995). This relation has been used to describe the development of a single economy on the long-term (Lindmark 2002, Egli 2004), and has also been tested among countries with different levels of income. The results obtained are controversial. For example, on richer countries like OECD ones, an inverted U-shape is found, but not on the poorer non-OECD countries, which show an increasing pattern (Galeotti et al. 2006). More rarely, it has been tested with micro data, for example in the case of UK (Giovanis 2013). He finds mixed results, the evidence of an EKC depending on the environmental indicator and the econometric model used. Finally, it has been studied also for specific fields of consumption, such as transport emissions (Cox et al. 2012). Still, at the individual level, little is known about how air pollution varies with income. Besides, whatever the form of the relationship and its conformity with the EKC hypothesis, taking into account the inequality content of environmental impact may be important at the moment of designing sustainable policies aimed at reducing greenhouse gas emissions (GHGEs).

In the French context, Combet et al. (2010) raised the question of equity in assessing the environmental impact and the consequent taxation issue. Several works show the variability of emissions according to socioeconomic characteristics of the household. The French shopping basket was estimated in 2009 to emit 1.4t CO_2 equivalent per year for one household (Boeglin et al. (2012). The variability of this figure according to occupation, family structure, or region was found to reach 20% deviation compared to the average value. In particular, blue-collars, or families with at least 3 children, or the northern region are the more emitting households. Chancel (2014) studied the generational effect through the impact of date of birth and income on French household GHGEs. Comparing emissions in the top and bottom decile households, he found around twice as much emissions in the top decile than in the bottom one.

This article aims at testing the EKC hypothesis for food consumption, which is a major source of emissions. Food is estimated to be responsible for 30% of GHGEs in Europe. Improving its sustainability potential is a main issue on the world environmental agenda and changes in diet and in purchase behavior seem unavoidable. Therefore, its relation with the level of income is an important issue. Food purchases have been estimated to emit around 1t CO2 eq per year per household (Boeglin et al. (2012)). Income disparities in the food purchase basket have been found among French households (Caillavet et al. 2009).These may lead to differentiated environmental impacts of food according to income, which have not been measured yet. Indeed, for each income class a different price per kg (obtained by dividing expenditure dedicated to purchases by the corresponding quantities) is found at the level of each food group, reflecting different purchase strategies in terms of quality of foods, origin of the products, amount purchased, distribution mode, packaging, … It is well-known that this price increases with income (Caillavet et al. 2009, Beatty 2010), and that a higher income favours a diet of higher nutritional quality (Darmon and Drewnowksi 2008). However, no specific relationship between income and environmental impact can be expected a priori. Recently, the environmental impact of the diet has been studied in the French case by Vieux et al. (2013) and Masset et al. (2014). They show a complex relationship between environment, nutritional characteristics of foods, and the foods composition of the diet. In this framework, the link with income-related patterns of consumption was not investigated.

The present study explores the relationship between income and environmental impact of food-at-home purchases at the consumer level. First, it provides estimations of GHGEs of purchases for food-at-home by income levels in France, thus allowing to test the Environmental Kuznets Curve hypothesis for this sector. Second, it highlights apparent contradictions between daily GHGEs and per calory GHGEs according to income. Third, it provides factors of explanation lying in the social patterns and the structure of food-at-home consumption.

This article is organized as follows. Section 2 describes the method and data used. Section 3 presents the results. Section 4 discusses main results. Section 5 concludes.

1. Methods

Data

For food-at-home *purchases*, we use Kantar Worldpanel data. This survey contains four-week food acquisitions for food-at-home consumption. It delivers quantities and expenditures for a wide range of food products. Unfortunately, data for food-away-from home are not registered. The households are selected by stratification according to several socioeconomic variables. All participating households register the grocery purchases through the use of bar codes. However, to alleviate its workload, each household is requested to register its purchases for a restricted set of products only. Consequently, the whole purchases for food-at-home are not available for each household.

Due to the structure of the data, we need to aggregate household on representative population groups (Allais et al., 2010) to take into account the whole purchases for food at-home and hence the total GHGEs. In order to capture income effects, life cycle effects, and regional heterogeneity, these population groups are constructed using the following variables:

1. Four income classes, based on family income corrected by consumption units (CU) according to OECD scale. Taking into account the demographic structure of the household, this scale counts 1 for a single adult, 0.7 for a supplementary adult and 0.3 for any member less than 15 years old. On this base, we obtain the following classes, corresponding to quartiles of household income per CU: modest, lower-average, upper-average, well-off households;

2. Four age groups based on the age of the household head: under 30 years old, 31-45, 46-60, over 61;

3. Three regions with significant differences over food-at-home purchases: Paris and its suburbs; the North and the East; the South and the West.

Hence we constructed 48 cohorts. For each cohort, purchases were observed for 169 periods of four weeks from 1998 to 2010. This gives 8112 observations representing purchases for 48 population groups.

To compute the GHGEs associated with food-at-home purchases, we aggregated food into 21 categories taking into account the range of environmental emissions and the nutritional contents of the products (according to Masset et al. 2014 results). In particular, food groups were differentiated according to their animal or plant-based content.

Environmental data were collected by Greenext, an environment consultancy, to assign the environmental impact of products through Life Cycle Analysis, using the ISO14040-44 standards: "compilation and evaluation of the inputs, outputs and the potential environmental impacts of product system throughout its life-cycle". The environmental impact indicator estimated therefore includes the impacts associated with each stage of the production, transformation, distribution, use, and end-of-life of food products. Using a top-down approach combining French trade and production data, the final value for several indicators reflects the average food product as consumed on the French market. The Greenext method is presented in more detail on their website (Greenext). The data set delivers for 311 products the environmental impact of producing these products through different indicators. In particular, they are illustrated by GHGEs (expressed in gram of CO_2 equivalent per 100grams), which is the main indicator used in the literature. Our analysis will focus on this indicator. It is used to convert quantity of food-at-home purchases into GHGEs associated with these purchases. These values are linked with the energy content of the food-at-home purchased, which requires additional information on nutrient content of food products.

The *energy content of food* comes from the CIQUAL nutritional table for more than 500 food products. This allows first to calculate the caloric content of food-at-home food purchases, and then to express the data for a given amount of calories, which enables to compare different food baskets at a normalized level of energy content. Since, the mean energy intake for adults is 2000kcal/day (European Parliament 2011), this level of caloric content was used as a reference for the normalization.

For each food group, we computed the amount of emissions on a daily basis by cohort. Then we aggregated the amount of emissions over the 21 food groups to deliver the total level of emissions for each cohort and each time period.

2. Results and Analysis

Descriptive statistics

The sociodemographic description of our sample, total and by income class (quartiles of household income per CU), is given in Table 1. We can characterize the modest households (1st quartile) with the usual socioeconomic status characteristics, compared with the well-off class (4th quartile): 80% live with a family income under 1500€/month, their reference person did not achieve in 82% of the cases the baccalaureate level (vs 31%), 36% are inactive or retired (vs 26%), 28% are blue collars (vs 5%). Sociodemographic variables indicate that the majority of modest households include children (68%) and 47% include at least one child under 16 years. Corresponding figures for well-off households are respectively 22% and 12%. Home-owners are less frequent (40% of modest households but 61% of well-off households). An interesting feature is in this context the higher proportion of kitchen gardens in modest households (46% vs 42%). It may in part correspond to the spatial distribution of the population: modest households live more in rural or weakly dense areas (36% vs 24%), and less in urban areas over 200,000 inhabitants (42% vs 55%). The level of home equipment is for some goods inferior compared to other income groups: on average, these households have at home less computers and less dishwashers.

These characteristics induce diet disparities, as shown in table 2 which presents the total energy content of each food group purchases for the whole sample, and per income classes.

The main sources of energy in food-at-home purchases come primarily from plant-based foods high in fats which represent 16.3% of calories for the poorest households and 15.7% for the richest households. Then dairy products, with a higher share of yogurts for the poorest households than for the richest (8.4% vs 7.7%), while we observe the opposite with cheese (7.6% vs 8.9%). Plant-based foods high in sugar contribute slightly more to total energy purchased in the richest class (7.5% vs 7.3%), while prepared desserts contribution is slightly lower (7.0% vs 7.3%). Among animal products, animal fats are the main source of calories and bring more to the poorest households (7.2% vs 7.0%). Among drinks, alcohol brings more energy in richest households (6.7% vs 6.4%) while it is the opposite in the case of soft drinks (5.2% vs 5.5%). On the whole, the total contribution of animal-based products to energy purchased does not vary with income: 45.6% for the poorest and 45.5% for the richest. In terms of normalized content, results are only slightly different and the hierarchy of products is not modified. However, note that for some food groups, the gap between lowest and highest income classes is amplified: this occurs for beef, cooked meats, yogurt and prepared desserts.

The corresponding GHGEs are presented in table 3, for the whole sample and per income classes. Total GHGEs due to food-at-home amount to 1.43 tons CO2 equivalent. Turning our GHGEs estimation into daily equivalent, we obtain 3.9kg per household. Expressed per 2000kcal, we find 2.5kg per household.

Estimations

We denote here e each environmental indicator or nutrient content, and we estimate the following equation for each e:

$$y_{ct}^{e} = \alpha_0 + \alpha_c + \sum_{j=1}^{K} \beta_j Z_{jct} + \varepsilon_{ct},$$

where y_{ct}^{e} denotes the log of total level of emission due to food purchases for cohort c and time t; Z_{jct} is a set of sociodemographic variables, and β_j sociodemographic parameters to be estimated; α_c is a cohort fixed effects which will be detailed in the following paragraphs; and ε_{ct} is the residual. This equation introduces a fixed effect per cohort as well as sociodemographic variables. Estimation results are presented in Table 4.

First, to focus on income disparities, we assume no age effects on emission, i.e. $\alpha_c = \sum_{inc=1}^{4} \alpha_{inc} I_{inc}$, where I_{inc} indicates each dummy variable for WO, UA, LA and MO (respectively Well-Off, Upper-Average, Lower-Average and Modest households). Second, we decompose α_c to measure both income and age disparities with cross interactions such that: $\alpha_c = \sum_{ia=1}^{16} \alpha_{ia} I_{ia}$, where I_{w} indicates income age interaction dummy variables. Third, we assume a potential regional effect by considering $\alpha_{iar} = \sum_{iar=1}^{48} \alpha_{iar} I_{iar}$. Finally, we run the same estimations for GHGEs expressed per 2000 kcal purchased .

Results

Income disparities in GHGEs per day

A first glance reveals income disparities in GHGEs due to food purchases. Per income class (table 3), we find that the well-off households purchases emit less GHG (3.4kg) than modest households (3.9kg). (Figure 1 : Adjusted Daily CO2 Emissions per Income Classes). A further regression analysis of GHGEs on the level of income per CU was statistically significant ($p<0.001$). The level of GHGEs was related positively to the 2 lower income groups (modest and lower-average), well-off households being the reference class (table 4, column 1).

Income disparities in GHGEs per 2000kcal

Regarding the level of GHGEs expressed for 2000kcal, it turns out to be the opposite: well-off households purchases show now higher GHGEs than modest households (2.6kg vs 2.5kg CO_2 equivalent). As observed in graph 2, GHGEs appear to increase with household income per CU. We find that income is still significant ($p<0.05$). However, the level of GHGEs is now observed to be negatively related to income. The estimated effect shows in this case a low value (table 4, column 2).

Income disparities in GHGEs per 2000 kcal, by age class

In order to separate the disparities due to differences in the lifecycle position from socioeconomic disparities, we computed the level of energy-related emissions according to income by age of the household head. Table 4, column 3 shows the presence of an age effect which is positively related with level of emissions: compared to the reference group of younger households (head under 30 years), older households, whose head is 45-60 and over 60, are associated with increased levels of emissions ($p<0.001$). Interactions between age and income are also found ($p<0.05$) and show a positive relationship of middle-age households (20-45 and 45-60) in lower-average income class with GHGEs. Consequently, even after adjusting on age and age-income interactions, lower income classes are still negatively related to the level of emissions when compared to the richer class (well-off households).

We represent in graph 3 the age-adjusted level of energy-related GHGEs by income class. We observe that income disparities exist at the level of each age group, in particular between well-off and modest households. However, in the cases of household heads over 30 years, the existence of significant disparities between the intermediate income classes (lower-average and upper-average households) is not always clear, as shown by overlapping of the confidence intervals.

Emission levels according to the structure of food purchases and income disparities

Table 3 shows the amount of GHGEs according to the structure of purchases disaggregated in 21 food groups.

At the global level as well as normalised by caloric content, the most impacting food groups are beef (838.41 gCO2eq/100g), alcohol (421.82g), and bottled water (418.55g). Though this hierarchy of impacting food groups remains similar by income class, their contribution to GHGEs may vary.

The contribution of foods with animal content to GHGEs is slightly higher for modest households than for well-off households, at the global level of emissions (51.3 vs 48.6%) as well as in normalized basis (49.3% vs 48.7%). In particular, for modest households purchases compared to well-off, the normalized CO2 impact is lower for several food groups, in particular: alcohol (11.0 vs 11.2%), fresh fruits and vegetables (2.6 vs 2.8%), plant-based foods high in sugar (2.4 vs 2.8%), fish (2.0 vs 2.2%), prepared dishes (2.0 vs 2.1%), while it is higher for several animal products: beef (21.8 vs 21.6%), cooked meats (4.4 vs 4.3%), animal fats (6.2 vs 5.9%), and also for starchy foods (2.8 vs 2.5%).

3. Discussion

Our estimation of total GHGEs for food at home which amounts to 1.43 tons CO2 equivalent can be compared to 1.4 tons CO2 equivalent estimated by Boeglin et al. for the current purchases basket of a French household (not restricted to food). When restricted to food, it would represent roughly 1 ton CO2-eq. A Swedish estimation finds 1.1 ton CO2-eq per capita (Wallen et al., 2004), therefore suggesting a higher value per household.

When considering our CO2 daily equivalent estimation (3.9kg per household), it appears lower than another estimation run on French full-diet data which amounts to 4.1kg per person (Vieux et al. 2012). However, contrary to our sample, this latter study includes consumption of food away from home. An estimation on UK data still obtains higher values since the average diet embodies 8.8kg CO2 equivalent per person (Hoolohan et al. 2013).

Our results evidence income disparities in the levels of environmental emissions caused by food purchases for food-at-home, which are statistically significant. From this, we draw a decreasing relationship between level of income and environmental impact caused by food. This is in tune with Boelgin's results based on occupation categories. Lower scale occupations: blue collars (+20%), white-collars, inactive other than retired, and farmers (all around +6%) have emissions above the average. Executives (-16%), intermediate occupations and retired (-5%) are under the average. In the framework of an EKC, it would correspond to the backward slope once the turning point has been overpassed.

But taking into account the caloric content of food purchases, which allows to normalize consumption with regards to density of the diet, turns out to be crucial since it produces a puzzling paradox: in fact, the decreasing trend with income per CU (graph 1: well-off households producing less CO2 (3.4kg) than modest households (3.9)) turns out to be an increasing trend with income per CU when dealing with emissions per 2000kcal. (graph 2: well-off households purchases show now a higher emission level of CO2 (2.6kg CO2 equivalent vs 2.5kg for modest ones)). In an EKC framework, an increasing slope would correspond to a pattern where consumption is still driven by more polluting goods when income is higher.

How can this paradox be explained ?

When it is not normalized by energy content, we find both a higher level of GHGEs and a higher calories content in modest households purchases than in richer households ones (tables 2 and 3). Indeed, our data show (table 2) that the energy content of purchases for modest households was higher than the well-off ones (3100 kcal vs 2637). A first explanation lies in different food patterns between food-at-home and food-away-from-home between these households. In a previous analysis of French budget data, Caillavet et al. (2009) observed that the budgetary share for food-at-home is higher for lower income households than for higher income groups. Richer households eat more frequently away from home.

One second element lies in the food structure of purchases according to income. When we compare the energy content of purchases between modest and well-off households (table 2), we observe for the former more calories coming from soft-drinks, plant-based foods high in fats, starchy food, meats other than beef, cooked meats, animal food high in fats, yogurt, prepared meals and desserts. Most of these food groups bring comparatively lower GHGEs than food groups overrepresented in well-off households purchases such as cheese, or fish, fresh fruits and vegetables.

Then, when we compare the levels of emissions associated to food groups according to income class (table 3), we find that higher energy is not necessarily equivalent to higher GHGEs, since purchases of modest households are more important in terms of energy content on low impacting groups such as soft drinks, yogurts, plant-based foods high in fats. In effect, these latter products are among the lowest values of the scale ranging food groups according to their level of GHGEs (see Masset et al. 2014 results). At the same time, food groups which are high producers of GHGEs such as cheese or fish, bring more calories to well-off households, what makes them higher contributors to GHGEs. This complex relationship between density in calories and environmental emissions is an important issue for income disparities.

Finally, the demographic structure of the households may differ among income classes and could explain part of the disparities in the structure of food purchases. This explains why the income effect is reduced when adjusting on age of the household head. This latter variable is a good indicator of the position of the household in the lifecycle and thus acts as a proxy for household composition (number of members, presence of children, working-age adults…).

4. Conclusions

Total GHGEs for food-at-home were found to reach 1.43 ton CO2 equivalent per household. Turning our estimation into daily equivalent, we obtain 3.9 kg CO_2 equivalent per household. Our estimation is consistent with other evaluations on French data, but remains lower than Swedish or UK evaluations for food consumption.

We test the EKC hypothesis by presenting estimations of GHGEs disaggregated by income class. We find that income disparities in GHGEs are statistically significant. Income disparities, when adjusted on age, are still significant though modest.

We take into account the compatibility of environmental objectives with health constraints and present estimations of GHGEs for a given level of caloric content. Thus, we find an interesting paradox: lowest income households show the highest level of GHGEs at the global level of purchases (+14.7% compared to well-off households), but the lowest level on an normalized 2000 kcal basis (- 9.6%). Consequently the relationship between environmental emissions and income is increasing at the global level, but decreasing when caloric-normalized. This suggests quite different positions on the EKC curve.

Our study faces several limits. Firstly, our estimation is based on purchases and restricts to food-at-home, which underestimates the scope of food consumption and therefore GHGEs. This underestimation is not neutral according to income, the richest households consuming a higher share of food-away-from home than poorest ones. Then, due to the structure of Kantar Worldpanel data, we had to build representative population groups to recover the full purchases amount, hence the total calories and total GHGEs amounts. In doing so, we had to average several key variables such as age, region, and family structure on 48 population subgroups, which reduces the variability of our sample. But it means that what we could measure is a benchmark estimation and that socioeconomic disparities are wider than what we observed. This strengthens the robustness of our conclusions.

Finally our analysis is based on a single indicator, GHGEs, while other parameters (water for example…) could be taken into account to better evaluate the environmental impact of foods. In particular, this could modify the characterization of the highest emitting income class. However Masset et al. found that air acidification and freshwater eutrophication indicators were strongly correlated with GHGEs.

In conclusion, in an EKC framework, the environmental impact of food purchases would be represented by a decreasing slope with income. However, our analysis shows how the structure of purchases differs between income classes and finds that, once caloric-normalized, this slope has an opposite trend, since richer households' purchases favour higher emitting food groups than lower income households.

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Table 1: Descriptive statistics

Variable	Total sample		Well-Off		Upper-Average		Lower-Average		Modest	
	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
Household income €/month										
[0; 900[	0.09	0.17	0.00	0.00	0.00	0.00	0.05	0.05	0.32	0.20
[900; 1500[	0.21	0.21	0.00	0.00	0.12	0.08	0.25	0.15	0.48	0.14
[1500; 2300[	0.25	0.17	0.18	0.14	0.23	0.11	0.43	0.12	0.18	0.15
[2300; 3000[	0.17	0.15	0.14	0.08	0.33	0.11	0.20	0.13	0.02	0.05
[3000; [	0.27	0.30	0.69	0.13	0.32	0.19	0.06	0.09	0.00	0.00
Education of head of household										
Low degree diploma	0.41	0.17	0.23	0.11	0.42	0.11	0.52	0.11	0.49	0.15
Level of baccalaureate	0.15	0.08	0.19	0.07	0.19	0.07	0.14	0.07	0.09	0.07
Baccalaureate and higher degree	0.24	0.21	0.50	0.16	0.25	0.14	0.11	0.08	0.09	0.11
Socio-professional category of head of household										
Farmer	0.01	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.03	0.04
Artisan	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03
Executive	0.12	0.15	0.30	0.18	0.13	0.08	0.05	0.04	0.02	0.03
Intermediary profession	0.19	0.14	0.26	0.16	0.24	0.14	0.17	0.09	0.08	0.06
Employee	0.18	0.12	0.11	0.07	0.19	0.11	0.22	0.12	0.20	0.12
Worker	0.17	0.15	0.05	0.05	0.13	0.08	0.23	0.15	0.28	0.18
Retired	0.26	0.36	0.26	0.36	0.27	0.37	0.26	0.36	0.24	0.36
Without child	0.52	0.33	0.78	0.15	0.59	0.25	0.40	0.34	0.32	0.32
With at least one child (<15)	0.32	0.30	0.12	0.12	0.26	0.23	0.42	0.33	0.47	0.32
Owner	0.52	0.24	0.61	0.24	0.56	0.24	0.50	0.22	0.40	0.23
Individual house	0.54	0.22	0.49	0.21	0.54	0.21	0.57	0.20	0.53	0.24
Kitchen garden	0.47	0.20	0.42	0.19	0.48	0.19	0.50	0.19	0.46	0.21
Household equipment										
Personal computer	0.63	0.28	0.71	0.23	0.66	0.25	0.59	0.28	0.54	0.30
Fryer	0.71	0.13	0.59	0.12	0.70	0.10	0.77	0.09	0.76	0.14
Dish washer	0.52	0.16	0.60	0.17	0.55	0.15	0.51	0.13	0.42	0.15
Freezer	0.48	0.15	0.41	0.15	0.47	0.14	0.53	0.13	0.52	0.16
One car	0.49	0.12	0.50	0.12	0.47	0.12	0.49	0.12	0.52	0.10
Two cars and more	0.40	0.18	0.43	0.17	0.46	0.17	0.41	0.19	0.29	0.16
Type of housing										
Rural area	0.20	0.13	0.16	0.11	0.18	0.11	0.22	0.12	0.25	0.16
Urban area from 2,000 to 10,000 inh.	0.10	0.06	0.08	0.05	0.10	0.05	0.12	0.05	0.11	0.06
Urban area from 10,000 to 50,000 inh.	0.10	0.05	0.10	0.07	0.10	0.04	0.11	0.04	0.10	0.05
Urban area from 50,000 to 200,000 inh.	0.11	0.08	0.11	0.09	0.12	0.08	0.11	0.08	0.11	0.08
Urban area 200,000 inh. and more	0.48	0.28	0.55	0.27	0.50	0.26	0.44	0.27	0.42	0.30
Nobs.	8112		2028		2028		2028		2028	

Table 2: Contribution of food groups to energy by income class

	Total				Well-off				Upper-Average				Lower-Average				Modest			
Food groups	Energy		Eq 2000kcal		Energy		Eq 2000kcal		Energy		Eq 2000kcal		Energy		Eq 2000kcal		Energy		Eq 2000kcal	
	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%
Juices	139.19	4.54%	88.89	4.44%	120.98	4.59%	90.70	4.54%	127.35	4.62%	91.27	4.56%	133.49	4.58%	90.05	4.50%	138.55	4.47%	87.17	4.36%
Alcohol	190.86	6.23%	122.21	6.11%	176.10	6.68%	130.52	6.53%	176.14	6.39%	125.14	6.26%	184.96	6.35%	125.21	6.26%	196.73	6.35%	124.60	6.23%
Soft drinks	163.67	5.34%	104.27	3.40%	137.97	5.23%	103.80	5.19%	142.98	5.19%	103.06	5.15%	151.25	5.19%	102.91	5.15%	171.30	5.53%	106.41	5.32%
Water	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00	0.00%
Coffee and tea	11.57	0.38%	7.76	0.25%	11.10	0.42%	8.53	0.43%	11.28	0.41%	8.32	0.42%	11.41	0.39%	8.03	0.40%	11.54	0.37%	7.70	0.39%
Fresh fruits and vegetables	36.12	1.18%	23.23	0.76%	33.35	1.26%	24.59	1.23%	34.40	1.25%	24.33	1.22%	34.91	1.20%	23.50	1.17%	36.29	1.17%	23.21	1.16%
Grains	50.23	1.64%	32.02	1.04%	48.80	1.85%	33.97	1.70%	49.38	1.79%	32.95	1.65%	48.56	1.67%	32.50	1.62%	51.34	1.66%	32.55	1.63%
Plant-based foods high in fats	490.99	16.02%	323.23	10.54%	413.37	15.67%	315.26	15.76%	431.24	15.65%	316.04	15.80%	459.24	15.76%	318.04	15.90%	504.88	16.28%	327.65	16.38%
Plant-based dishes	120.17	3.92%	78.98	2.58%	106.03	4.02%	81.24	4.06%	110.14	4.00%	80.46	4.02%	115.33	3.96%	79.94	4.00%	121.07	3.91%	78.80	3.94%
Plant-based foods high in sugar	224.25	7.31%	147.61	4.81%	197.36	7.48%	150.49	7.52%	204.62	7.43%	149.36	7.47%	213.64	7.33%	147.65	7.38%	227.60	7.34%	148.69	7.43%
Starchy foods	182.52	5.95%	119.41	3.89%	151.85	5.76%	116.24	5.81%	160.92	5.84%	117.53	5.88%	172.65	5.93%	118.84	5.94%	183.31	5.91%	118.70	5.93%
Processed fruits and vegetables	44.86	1.46%	29.69	0.97%	40.30	1.53%	30.94	1.55%	41.42	1.50%	30.48	1.52%	43.34	1.49%	30.11	1.51%	45.26	1.46%	29.74	1.49%
Beef	101.34	3.31%	66.04	2.15%	88.00	3.34%	67.01	3.35%	90.59	3.29%	66.01	3.30%	96.68	3.32%	66.50	3.33%	103.43	3.34%	66.57	3.33%
Other meats	109.63	3.58%	71.37	2.33%	91.32	3.46%	69.27	3.46%	95.12	3.45%	69.16	3.46%	103.52	3.55%	70.87	3.54%	111.95	3.61%	71.98	3.60%
Cooked meats	76.22	2.49%	49.70	1.62%	62.95	2.39%	47.99	2.40%	66.48	2.41%	48.40	2.42%	71.90	2.47%	49.29	2.46%	77.02	2.48%	49.69	2.48%
Animal-based foods high in fats	222.21	7.25%	142.67	4.65%	183.19	6.95%	137.26	6.86%	194.55	7.06%	139.23	6.96%	211.24	7.25%	142.50	7.12%	221.82	7.15%	140.88	7.04%
Cheese	236.53	7.72%	157.71	5.14%	235.89	8.94%	181.05	9.05%	237.62	8.63%	174.18	8.71%	236.89	8.13%	165.38	8.27%	234.43	7.56%	156.92	7.85%
Fish and seafoods	36.25	1.18%	24.22	0.79%	33.90	1.29%	26.04	1.30%	34.22	1.24%	25.21	1.26%	35.28	1.21%	24.67	1.23%	36.90	1.19%	24.59	1.23%
Yogurts	262.20	8.55%	170.68	5.57%	201.68	7.65%	153.17	7.66%	223.25	8.10%	162.62	8.13%	243.83	8.37%	166.55	8.33%	259.00	8.35%	165.36	8.27%
Prepared mixed meals	140.70	4.59%	93.45	3.05%	118.34	4.49%	91.75	4.59%	124.51	4.52%	92.08	4.60%	132.06	4.53%	92.13	4.61%	143.16	4.62%	94.45	4.72%
Prepared desserts	227.01	7.40%	147.35	4.81%	185.31	7.03%	140.54	7.03%	199.02	7.22%	144.34	7.22%	213.58	7.33%	145.53	7.28%	226.72	7.31%	145.36	7.27%
Energy content (kcal/day)	**3065.77**	**100%**	**2000.00**	**100%**	**2637.31**	**100%**	**2000.00**	**100%**	**2754.98**	**100%**	**2000.00**	**100%**	**2913.50**	**100%**	**2000.00**	**100%**	**3100.36**	**100%**	**2000.00**	**100%**

Table 3: Contribution of food groups to CO2 Emissions by income class

	Total				Well-off				Upper-Average				Lower-Average				Modest			
Food groups	Emissions		Eq 2000kcal		Emissions		Eq 2000kcal		Emissions		Eq 2000kcal		Emissions		Eq 2000kcal		Emissions		Eq 2000kcal	
	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%	mean	%
Juices	319.98	8.21%	204.34	8.08%	278.17	8.05%	208.55	8.01%	292.78	8.21%	209.84	8.16%	306.87	8.19%	206.99	8.09%	318.51	8.09%	200.38	7.93%
Alcohol	421.82	10.82%	270.63	10.71%	393.45	11.39%	291.69	11.20%	390.04	10.94%	277.18	10.78%	411.31	10.98%	278.83	10.90%	435.76	11.06%	276.93	10.95%
Soft drinks	176.21	4.52%	111.94	4.43%	151.58	4.39%	113.51	4.36%	156.36	4.38%	112.28	4.37%	164.03	4.38%	111.33	4.35%	183.90	4.67%	113.88	4.50%
Water	418.55	10.73%	270.85	10.72%	358.09	10.37%	272.55	10.47%	380.30	10.66%	275.99	10.73%	397.02	10.60%	271.78	10.62%	417.87	10.61%	266.49	10.54%
Coffee and tea	14.13	0.36%	9.44	0.37%	11.92	0.34%	9.22	0.35%	12.39	0.35%	9.24	0.36%	13.23	0.35%	9.28	0.36%	14.56	0.37%	9.59	0.38%
Fresh fruits and vegetables	103.92	2.67%	66.92	2.65%	99.73	2.89%	73.39	2.82%	101.70	2.85%	71.89	2.79%	102.00	2.72%	68.63	2.68%	103.86	2.64%	66.71	2.64%
Grains	101.04	2.59%	65.74	2.60%	95.83	2.77%	70.02	2.69%	98.29	2.76%	68.69	2.67%	98.10	2.62%	66.97	2.62%	101.55	2.58%	65.84	2.60%
Plant-based foods high in fats	95.17	2.44%	62.71	2.48%	81.10	2.35%	61.89	2.38%	84.42	2.37%	61.89	2.41%	89.62	2.39%	62.06	2.43%	97.41	2.47%	63.35	2.51%
Plant-based dishes	65.05	1.67%	42.91	1.70%	65.09	1.88%	49.02	1.88%	65.01	1.82%	47.12	1.83%	64.78	1.73%	44.66	1.75%	65.48	1.66%	43.05	1.70%
Plant-based foods high in sugar	89.83	2.30%	59.30	2.35%	94.72	2.74%	71.79	2.76%	92.56	2.60%	67.17	2.61%	91.20	2.43%	63.13	2.47%	90.62	2.30%	60.09	2.38%
Starchy foods	107.69	2.76%	70.96	2.81%	83.21	2.41%	64.63	2.48%	91.09	2.55%	67.18	2.61%	99.19	2.65%	68.87	2.69%	108.31	2.75%	70.49	2.79%
Processed fruits and vegetables	70.40	1.81%	46.86	1.85%	63.28	1.83%	48.77	1.87%	65.54	1.84%	48.32	1.88%	68.41	1.83%	47.70	1.86%	70.13	1.78%	46.46	1.84%
Beef	838.41	21.50%	548.08	21.68%	738.58	21.38%	562.35	21.60%	756.95	21.23%	551.79	21.45%	806.04	21.51%	555.00	21.69%	852.46	21.64%	551.69	21.82%
Other meats	200.76	5.15%	130.45	5.16%	177.58	5.14%	133.84	5.14%	182.78	5.13%	131.90	5.13%	193.13	5.15%	131.86	5.15%	203.18	5.16%	130.98	5.18%
Cooked meats	172.57	4.43%	112.25	4.44%	145.98	4.23%	110.81	4.26%	153.03	4.29%	110.93	4.31%	164.88	4.40%	112.76	4.41%	173.22	4.40%	111.63	4.42%
Animal-based foods high in fats	248.81	6.38%	159.68	6.32%	205.76	5.96%	154.00	5.91%	218.38	6.12%	156.17	6.07%	236.81	6.32%	159.64	6.24%	248.18	6.30%	157.55	6.23%
Cheese	35.10	0.90%	21.29	0.84%	28.77	0.83%	20.39	0.78%	30.99	0.87%	21.13	0.82%	33.39	0.89%	21.27	0.83%	34.57	0.88%	20.57	0.81%
Fish and seafoods	74.32	1.91%	49.53	1.96%	73.29	2.12%	56.06	2.15%	72.62	2.04%	53.01	2.06%	73.81	1.97%	51.42	2.01%	75.51	1.92%	50.70	2.01%
Yogurts	11.01	0.28%	5.38	0.21%	11.49	0.33%	6.46	0.25%	11.54	0.32%	6.23	0.24%	11.35	0.30%	5.82	0.23%	10.62	0.27%	5.16	0.20%
Prepared mixed meals	74.51	1.91%	48.93	1.94%	71.39	2.07%	53.71	2.06%	71.96	2.02%	52.13	2.03%	73.15	1.95%	50.22	1.96%	75.30	1.91%	49.22	1.95%
Prepared desserts	260.66	6.69%	169.85	6.72%	225.58	6.53%	171.30	6.58%	237.54	6.66%	172.31	6.70%	248.93	6.64%	170.30	6.66%	260.43	6.61%	168.40	6.66%
CO2 Emissions (g eq. CO2/day)	**3899.14**	**100%**	**2527.52**	**100%**	**3454.30**	**100%**	**2603.76**	**100%**	**3566.14**	**100%**	**2572.30**	**100%**	**3747.10**	**100%**	**2558.40**	**100%**	**3939.34**	**100%**	**2528.09**	**100%**

Table 4: Estimation results

Variables	Log(CO_2 emissions)		Log(CO2 emissions eq. 2000 kcal)		Log(CO2 emissions eq. 2000 kcal)	
Well-Off	Ref.		Ref.		Ref.	
Upper-Average	0.067		-0.023		-0.036	***
Lower-Average	0.161	***	-0.034	*	-0.060	***
Modest	0.231	***	-0.062	***	-0.079	***
Age -;30]					Ref.	
Age]30;45]					0.014	
Age]45;60]					0.059	***
Age]60;+					0.067	***
Well-Off * Age -;30]					Ref.	
Well-Off * Age]30;45]					Ref.	
Well-Off * Age]45;60]					Ref.	
Well-Off * Age]60;+					Ref.	
Upper-Average * Age -;30]					Ref.	
Upper-Average * Age]30;45]					0.014	
Upper-Average * Age]45;60]					0.021	
Upper-Average * Age]60;+					0.016	
Lower-Average * Age -;30]					Ref.	
Lower-Average * Age]30;45]					0.032	*
Lower-Average * Age]45;60]					0.034	*
Lower-Average * Age]60;+					0.038	
Modest * Age -;30]					Ref.	
Modest * Age]30;45]					0.044	*
Modest* Age]45;60]					0.027	
Modest * Age]60;+					-0.004	
Intercept	8.112	***	7.859	***	7.824	***
Nobs	8112		8112		8112	

Note: * p<0.05, ** p<0.01, ***p<0.001

Figure 1 : Adjusted Daily CO2 Emissions per Income Classes

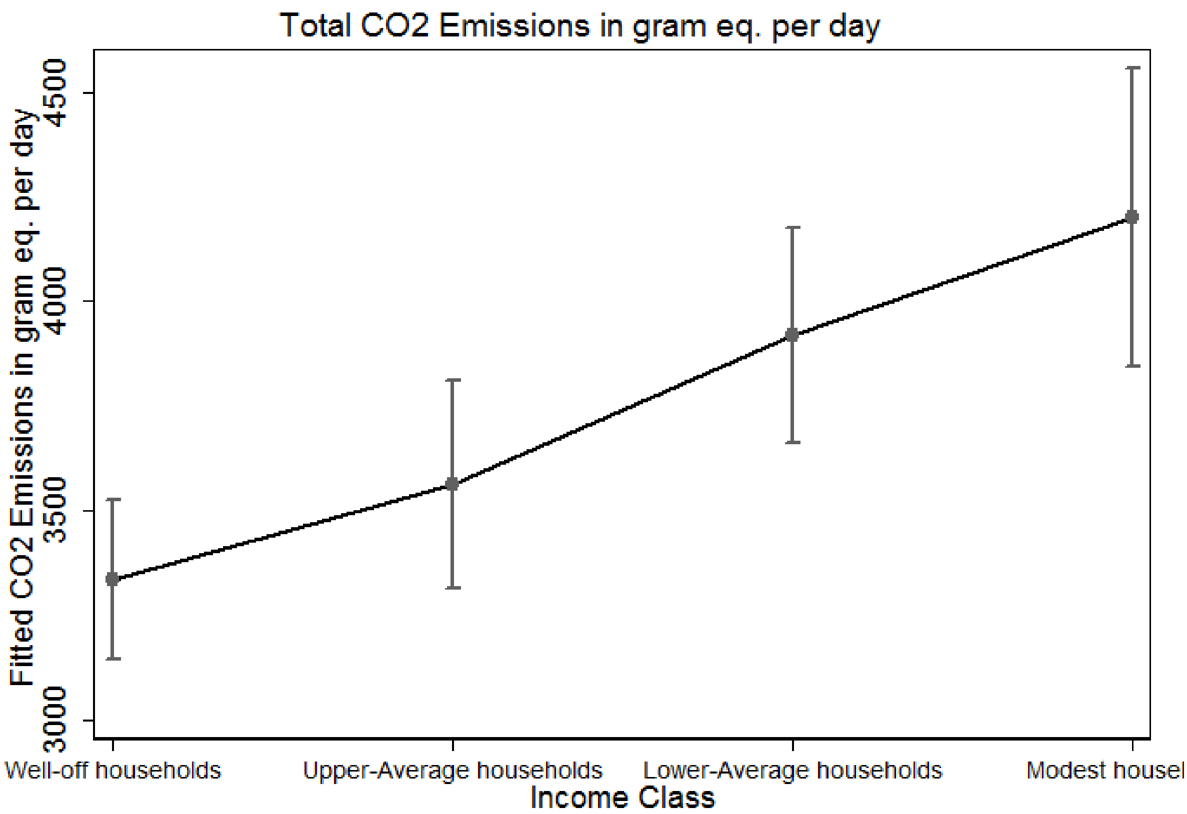

Figure 2 : Adjusted Daily CO2eq/2000kcal Emissions per Income Classes

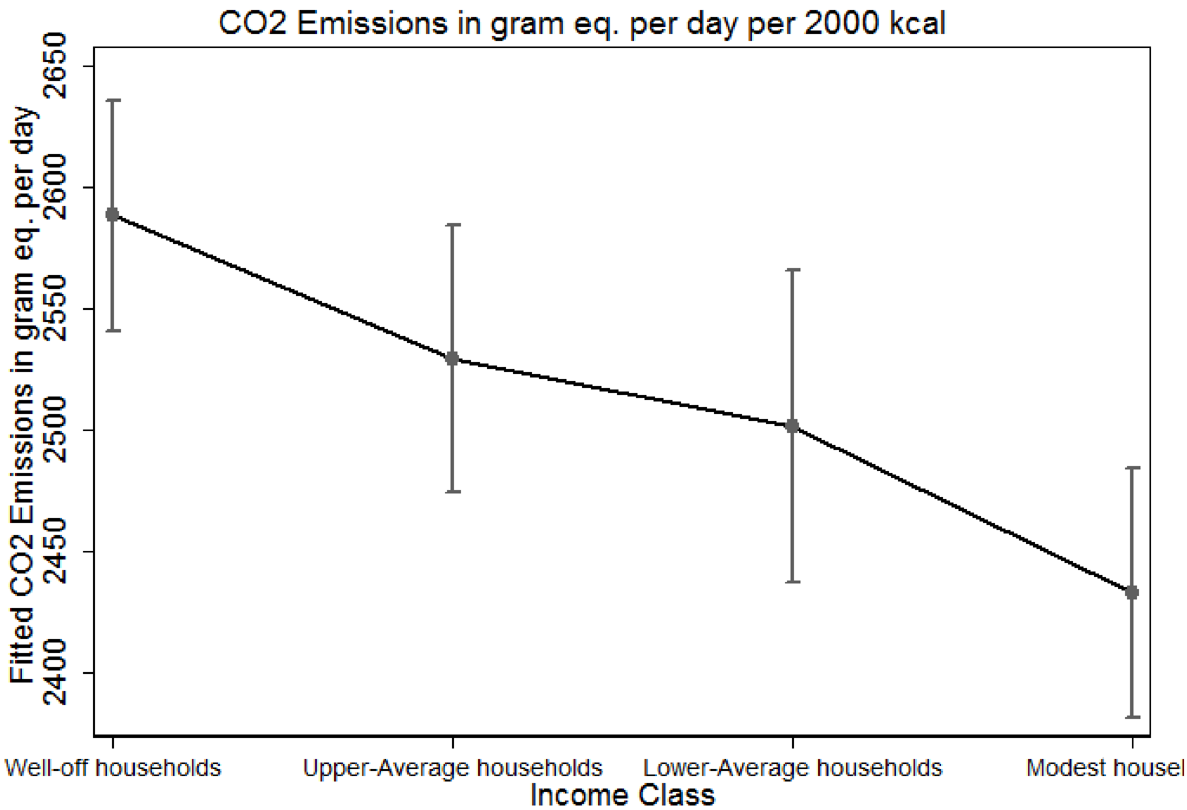

Figure 3: Adjusted Daily CO2eq/2000kcal Emissions per Income and Age Classes