Households' Food Carbon Footprint

Ondine Berland

Paris-Saclay University: INRAE & AgroParisTech

August 29, 2024

Food demand matters

Food consumption significantly contributes to household carbon emissions

🇫🇷 25% (Barbier et al., 2019) & 🇺🇸 20% (FAO)

Food production is emitting (farm, land use, processing)

Solely focusing on supply-side measures is insufficient to meet climate mitigation targets. (Frank et al., 2018, Costa et al., 2022)

- Shifts in production systems or relocation through international trade (estimated to reduce emissions by less than half of what is needed)

$\Rightarrow$ Need to change food demand for limiting global warming

Composition of food demand

Food demand is shaped by **budget constraints** and **preferences**. Food represents a large share of household expenditures

🇫🇷 16% (INSEE) & 🇺🇸 11% (USDA)

A **bundle** of (many!) **food goods** (≈ 200k products possible) with (very!) **heterogeneous emission** intensities (0.01 to 50 kg CO2 per kg of food)

1. **How much do food baskets emit?**

2. **How are food emissions affected by changes in expenditure and prices?**

What I do ▸ Literature

1. **How much do food baskets emit?**

   Scanner data to link food purchase and food emissions

   - Evidence for France
   - Substantial heterogeneity across product categories and emitters
   - No correlation between income and food emissions

2. **How are food emissions affected by changes in expenditure and prices?**

   Model the composition of food baskets

   - Estimate the model in the data
   - Heterogeneity in reaction to shocks across emitters types
   - Application: carbon tax simulation

From food purchases to environmental impacts

Purchase Data (Kantar)

Brand: Kinder,
Food group: chocolate
Chocolate type: with milk
Format: bar
Volume: 100g

Matching

Environmental Data (Agribalyse)

Food group: chocolates products
Label: chocolate snack bar, dairy filling
Climate change: 8.13 kg CO2 eq/kg

RESULT

Product category: Snacks
Weight: 0.1 kg
Climate change: 0.813 kg CO2 eq

Figure: Simple example from the snacks category.
(Fictitious Kantar attributes are displayed.) ML Matching

Data output

For any observed transaction

- Purchase date (Kantar 2017-2019)

  Quarterly aggregation

- Purchase information: expenditure, volume, characteristics

  Product category aggregation

- Environmental impact in CO2 eq kg/kg purchased (Agribalyse)

  Emission intensity per household at the category level

- Household information: (yearly socio-demographics)

Stylized Facts

- Heterogeneity across and within product categories ▸ Histogram
- Distribution of food carbon footprints across households ▸ Cummulative
- Sociodemographics and Food emissions ▸ Table
- No correlation between Income and Food emissions ▸ Binscatter

Food Basket Composition and CO_2 emissions

How do food-related emissions react to changes in prices and expenditure?

Quantify households' elasticities to prices and expenditures

Model households' food basket composition: Structural Demand model

Framework

Household i spends X_{ij} for quantity V_{ij} of good j

Observed prices P_{ij}

Food Expenditure: $X_i = \sum_j V_{ij} \times P_{ij}$

are linked with Food Emissions: $CO2_i = \sum_j V_{ij} \times CO2_{ij}$

Main equation (budget share)

Almost ideal demand model (Deaton and Muellbauer, 1980)

$$s_{ijt} = \sum_{j'} \gamma_{jj'} \ln P_{ij't} + \beta_j \ln\left(\frac{X_{it}}{P}\right) + \Pi Z_{it} + \epsilon_{ijt}$$

- household **i**, product category **j**, period **t**
- $s_{ijt} = \frac{X_{ijt}}{X_{it}}$ expenditure share per product category
- P_{ijt} Price per category ▸ Stone price indices
- Z_{it} Demand shifters
  - Control variables: age, car ownership, education, household size.
  - Regional x Period dummies.

Main equation (budget share)

Almost ideal demand model (Deaton and Muellbauer, 1980)

$$s_{ijt} = \sum_{j'} \gamma_{jj'} \ln P_{ij't} + \beta_j \ln\left(\frac{X_{it}}{P}\right) + \Pi Z_{it} + \epsilon_{ijt}$$

$\rightarrow$ β_j capture expenditure effects $\rightarrow \eta_{jX} = \frac{\partial s_j}{\partial X} \cdot \frac{X}{s_j}$

$\rightarrow$ $\gamma_{jj'}$ are price effects $\rightarrow \eta_{jj'} = \frac{\partial s_j}{\partial p_{j'}} \cdot \frac{p_{j'}}{s_j}$

Identification

'Observed' Price Endogeneity

→ Leave-one-out prices per category at the living zone level: P_{-itj}

- Within the living zone, at the food category level: conditional on controls and fixed effects, price variation assumed not correlated with residual demand variation.

Expenditure Endogeneity:

→ IV: income per consumption unit (Banks et al., 1997). F-stat>200

- Income only affects budget shares via food expenditure (conditional on controls and fixed effects)

Heterogeneity in reactions along the emission distribution

$\hat{\eta_{jX}}$: expenditure elasticity, $\hat{\eta_{jj}}$: uncompensated price elasticity.

	Bottom emitting quartile		Top emitting quartile	
	$\hat{\eta_{gX}}$	$\hat{\eta_{gg}}$	$\hat{\eta_{gX}}$	$\hat{\eta_{gg}}$
Red meat	0.554**	-1.093***	0.973***	-1.441***
	(0.192)	(0.034)	(0.107)	(0.029)
White meat	0.705***	-0.693***	0.769***	-0.915***
	(0.144)	(0.040)	(0.084)	(0.023)
Fish	1.236***	-0.820***	2.193***	-0.917***
	(0.121)	(0.023)	(0.164)	(0.034)
Dairy	1.184***	-0.851***	1.013***	-1.025***
	(0.070)	(0.017)	(0.064)	(0.017)
Fresh fruits & veg	1.679***	-0.966***	1.844***	-1.298***
	(0.081)	(0.050)	(0.119)	(0.046)
...	...	...	...	...

Table: Demand estimates top and bottom emission quartiles

Counterfactual Exercise

- Measure policies' effects on food emissions
- Account for the composition of the food's basket
- Carbon tax simulation (44.6 euro/ ton of CO_2) French carbon tax

Partial Equilibrium Setting

- Predict the new budget shares per category

$$s_{ij} = \sum_{j'} \hat{\gamma}_{jj'} \ln P_{ij'} + \hat{\beta}_j \ln\left(\frac{X_i}{P}\right) + \hat{\Pi} Z_i$$

Assumptions:

- No supply reaction
- No composition effect within categories

Predicted changes in emissions

Decrease in emissions of 2.5% (real expenditure constant)

Reduction mainly of red-meat related emissions

Larger reaction of the high-emitting quartile Graph

Trade-off:

- Nutrition: 2% increase in calories

Households' Food Carbon Footprint

1. **Describe food emissions at the household level**
   - Evidence from France: match purchase data w/ environmental info
   - Substantial heterogeneity across product categories and emitters
   - No correlation between income and food emissions
2. **Predict adjustment of food-related emissions to price variations**
   - Structural demand model to study choices across categories
   - High emitters are more price elastic (especially for top-emitting good)
   - 44.6euros/tCO2eq carbon tax on food could reduce total emissions by 2.5%

Appendix

References I

André, M., Bourgeois, A., Combet, E., Lequien, M., and Pottier, A. (2024). Challenges in measuring the distribution of carbon footprints: The role of product and price heterogeneity. Ecological Economics, 220:108122.

Banks, J., Blundell, R., and Lewbel, A. (1997). Quadratic engel curves and consumer demand. Review of Economics and Statistics, 79(4):527–539.

Barbier, C., Couturier, C., Pourouchottamin, P., Cayla, J.-M., Silvestre, M., and Pharabod, I. (2019). L'empreinte énergétique et carbone de l'alimentation en france. Club Ingénierie Prospective Energie et Environnement, Paris, IDDRI, 24p.

Berland, O. and Etilé, F. (2022). How do households adjust food purchases to fuel prices shocks? evidence from france. Evidence from France (July 5, 2022).

Bonnet, C., Bouamra-Mechemache, Z., and Corre, T. (2018). An environmental tax towards more sustainable food: empirical evidence of the consumption of animal products in france. Ecological economics, 147:48–61.

Caillavet, F., Fadhuile, A., and Nichèle, V. (2019). Assessing the distributional effects of carbon taxes on food: Inequalities and nutritional insights in france. Ecological Economics, 163:20–31.

References II

Chanut, N. (2021). The heterogeneous carbon content of food consumption and its implication for policy. Technical report.

Costa, C., Wollenberg, E., Benitez, M., Newman, R., Gardner, N., and Bellone, F. (2022). Roadmap for achieving net-zero emissions in global food systems by 2050. Scientific reports, 12(1):15064.

Deaton, A. and Muellbauer, J. (1980). An almost ideal demand system. The American economic review, 70(3):312–326.

Frank, S., Beach, R., Havlík, P., Valin, H., Herrero, M., Mosnier, A., Hasegawa, T., Creason, J., Ragnauth, S., and Obersteiner, M. (2018). Structural change as a key component for agricultural non-co2 mitigation efforts. Nature Communications, 9(1):1060.

Funke, F., Mattauch, L., Bijgaart, I. v. d., Godfray, H. C. J., Hepburn, C., Klenert, D., Springmann, M., and Treich, N. (2022). Toward optimal meat pricing: is it time to tax meat consumption? Review of Environmental Economics and Policy, 16(2):219–240.

Griffith, R., O'Connell, M., and Smith, K. (2016). Shopping around: how households adjusted food spending over the great recession. Economica, 83(330):247–280.

References III

Nevo, A. (2011). Empirical models of consumer behavior. Annu. Rev. Econ., 3(1):51–75.

Pottier, A. (2022). Expenditure elasticity and income elasticity of ghg emissions: A survey of literature on household carbon footprint. Ecological Economics, 192:107251.

Ruhm, C. J. (2000). Are recessions good for your health? The Quarterly Journal of Economics, 115(2):617–650.

Kantar World Panel Data

HomeScan Data: 20k consumers (unbalanced panel) over 10 years+

Transaction-level data

- Purchase characteristics (date, expenditure, volumes, retailer)
- Product characteristics (brand, organic, size)

Yearly socio-demographics

- Household-level (income level, size, location, durable goods)
- Individual-level (age, education, weight)
- **Note**: no info about intra-household allocation

Back

Agribalyse data

Open data produced by ADEME & INRAE since 2013

Life-cycle analysis

- From cradle to fork
- Multi-stages indicators (e.g. agriculture, transport, packaging, etc.)
- Multi environmental criteria (e.g. climate change, water quality, etc.)

2,500 food products

- Standardised products (e.g. plain yoghurt, fruit yoghurt, etc.)
- Representative of the French diet
- Frequent add-ups

Back

Emissions at Different Production Stages

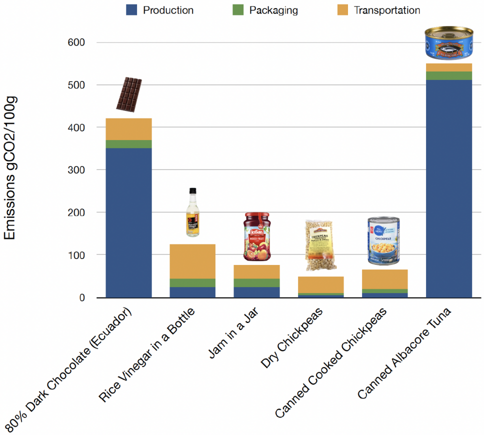


Figure: Examples of the distribution of emission across different production stages. (Source: Agribalyse 2017) Back

Ciqual data

Open data produced by ANSES since 2008

Nutritional data

- **Nutritional composition**

  lipids, proteins, carbohydrates, sugars, fatty acids, salt, vitamins and minerals

Link with food purchase data:

- **Fully matched** with Agribalyse
- Used to explore diet quality

Back

Systematic matching using ML

Starting point: existing matching for (French) Kantar 2010 & Agribalyse

→ Challenge: Evolution of products in Kantar

- Using existing matching to train Random Forest Algorithm
- Based on attributes (treated as binary (e.g. with chocolate? yes/no)

→ Final outcome: for every Kantar product - 'best fit' amongst 1k products

Matching graph | Random forests | Back

Random forests key concepts

Aim: find the best split to subset the data by maximising information gain

- **Definition**: algorithm combining the output of multiple **(simple)** decision trees to predict a single result.
- **Decision tree**: starts w/ product label, a sequence of yes/no answers based on a single or combination of features.
- **Tree bagging/bootstrapping**: every random forest contains trees formed on different subsamples (random sampling w/ replacement).
- **Feature sampling**: randomly select the features in the decision tree.
- **Majority voting**: usually average over trees to find the best (most likely) fit.
- **Stratification**: weighting to preserve the proportion of target classes as in the original dataset.

Supervised Machine Learning II

Choices:

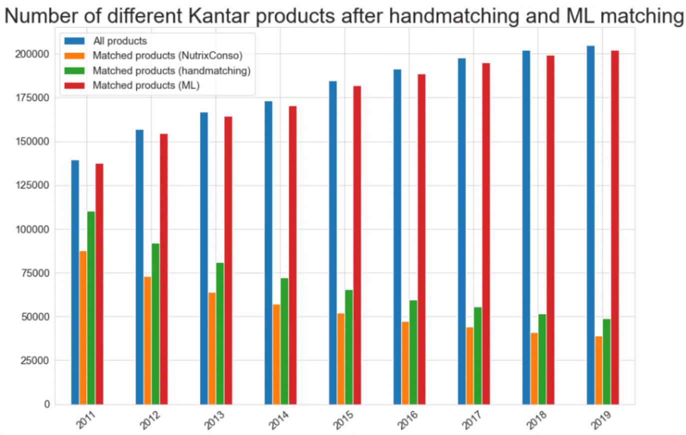
- RF: simple algorithm, common for classification, $\sim$ fast training
- Two features max per tree
- Drop 23 AGB classes that contain only 1 Kantar product in the training set.
- Training set 70%, testing set 30%

Measures of performance: 1000 decisions trees, 10 random samplings

- **Accuracy-score**=0.96 on testing set
- **F1-score**$<$0.6 for 13 AGB products only (out of $>$1k)

Back

Matching



Back

SF I: Large heterogeneity across products categories

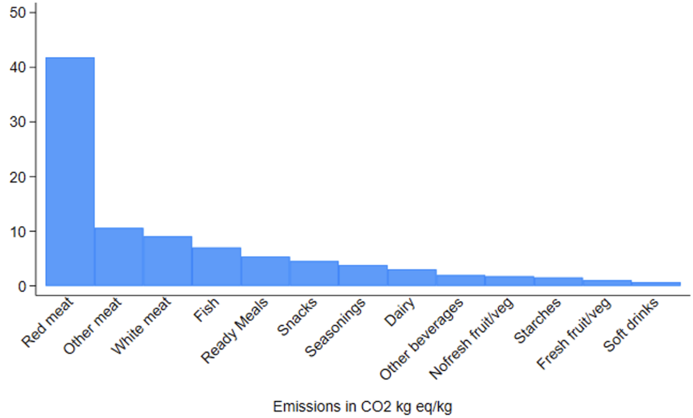


Figure: Emissions intensities per kilo of food.

SF I: Large heterogeneity across & within products categories

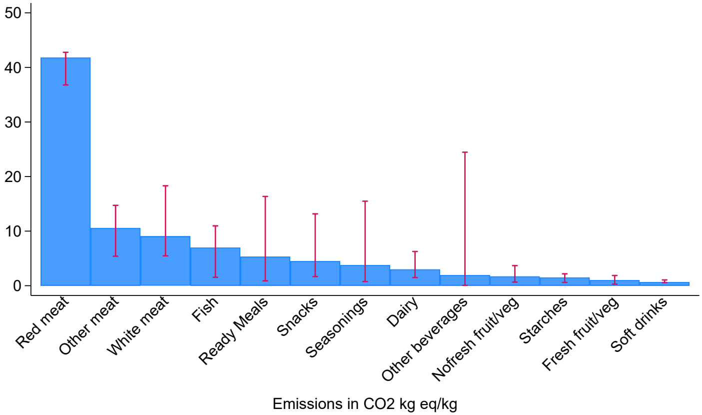


Figure: Emissions intensities per kilo of food.

Notes: Bars show 10 and 90 percentiles ANOVA Back

SF II: Substantial household heterogeneity in food emissions

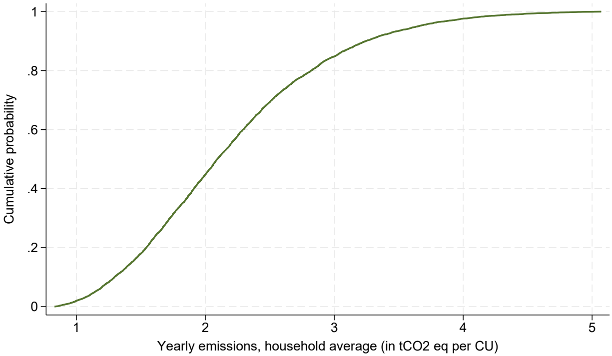
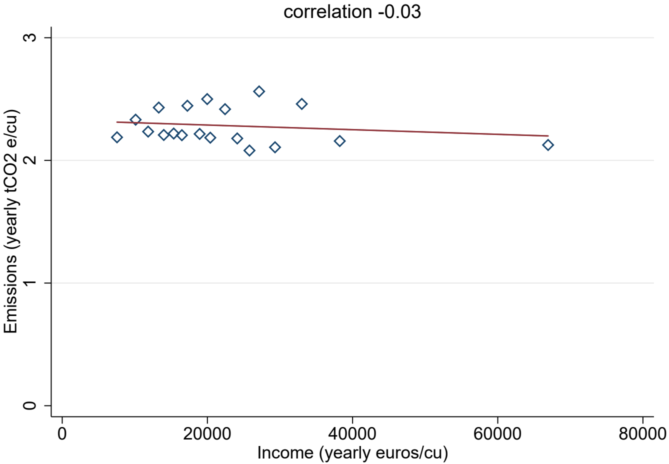


Figure: Distribution of yearly emissions per household.

▸ Lorenz curve of food emissions ▸ Compare emissions per CU vs per capita ▸ Back

No correlation between Income and Food Emissions



Household composition | Income & diets | Alternative dataset | Back

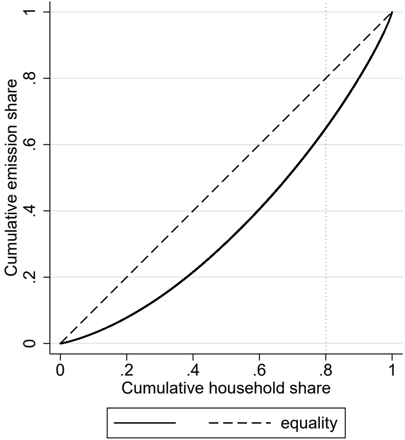
Emission Intensity Variation

Share of variance for different product categories	Within	Between
Product subgroup (N=180)	17.3	82.7
Product category (N=13)	43.2	56.8

Notes: This table presents the decomposition of carbon intensity variation between group variation and the within-group variation for two product aggregation levels.

Back to SF Back to Model choice

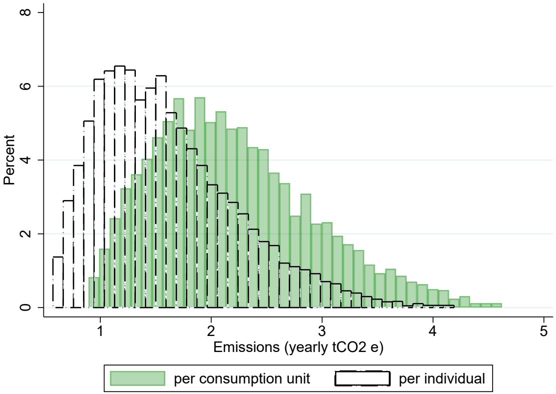
SF II: All food diets pollute



▸ Back

Figure: Lorenz curve of yearly total emissions per CU. Gini = 0.3

SF II: Comparisons emissions per CU and per capita



Back

Figure: Distribution of yearly emissions per household.

SF III: Heterogeneity in Emitters' Profiles

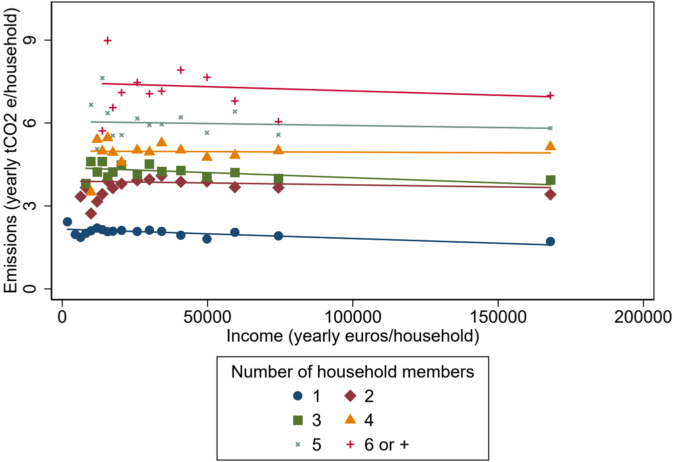
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	Mean/(SE)	Mean/(SE)	Mean/(SE)	Mean/(SE)
Income/CU	1934.09	1824.30	1760.64	1780.40
	(1341.24)	(1135.51)	(906.81)	(961.58)
Monthly Purchased Volumes/CU	48.89	60.40	73.40	104.32
	(57.94)	(63.29)	(78.52)	(169.36)
Age	51.25	54.70	58.00	61.68
	(17.42)	(17.49)	(15.20)	(14.19)
Car owner (0/1)	0.85	0.87	0.91	0.91
Education	2.76	2.58	2.43	2.23
	(0.91)	(0.87)	(0.84)	(0.74)
Obs	2161	2160	2160	2160

Notes: /CU indicates that values are divided by the number of consumption units in the household.

Table: Households' characteristics by emission quartile.

▸ More SES ▸ SES non-causal ▸ Covid year ▸ Back

No Correlation between Income and Food Emissions



Back

Alternative Dataset: Income and Total Food Emissions

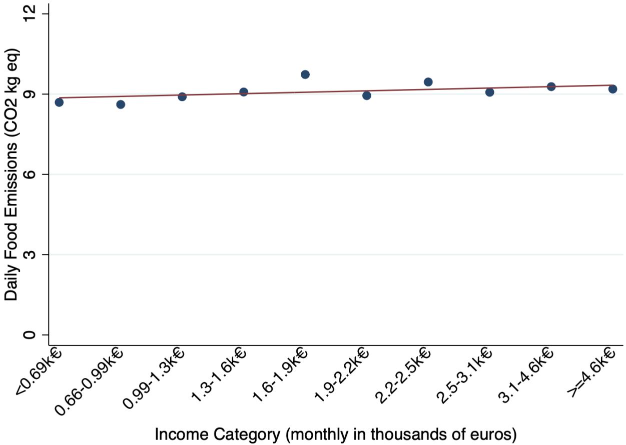


Figure: Source: INCA3 data (2017) and Agribalyse 2017.

Notes: Sample of 2,121 respondents (individuals) observed on a representative day, sample weights are used. Back

Censoring

Censoring across categories:

- Alcohol is also frequently censored. It is excluded from the analysis.
- Red meat is the second most censored category.

Time aggregation (Panel Years 2017 and 2019). For 13 product categories:

- Monthly: positive sample = 35% of total observations (household-time period pairs)
- Bimonthly: positive sample = 62%
- Quarterly: positive sample = 72%
- Biyearly: positive sample = 100%

Back

Stone price indexes

Definition: Stone price index is a linear approximation of the (non-linear) AIDS price index.

Use: helps ease computations and is not determinant for the results (Nevo, 2011).

Formally: Stone price index of a good category j composed of G goods, for household i

$$p_{i,j} = \sum_{g} s_{i,g} \ln\left(\pi_{i,g}\right),$$

- $s_{i,g}$ the household budget share of good g for category j
- $\pi_{i,g}$ the unit value of the good

Note that: goods refer to Kantar subgroups (within red meat: beef, mutton and lamb).

Back

Income and Food Basket Composition

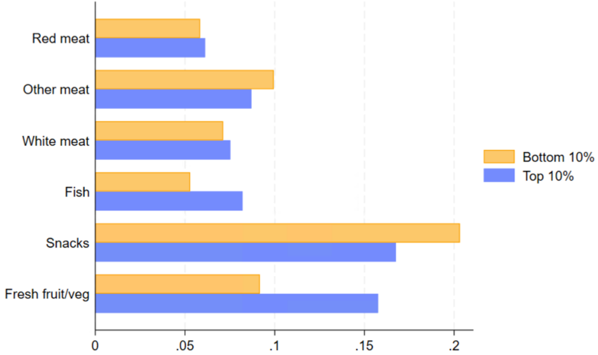


Figure: Distribution of budget shares by income decile ▸ Back

French Carbon Tax Simulation

$$P'_{i,j} = P_{i,j} + \tau_{CO2(j)} \text{ with tax rate } = 44.6 \text{ euro per ton of CO2}$$

$$\tau_{CO2(j)} = \text{Price Increase per kg} = \text{CO2 Intensity per kg} \times \text{Tax Rate per kg CO2}$$

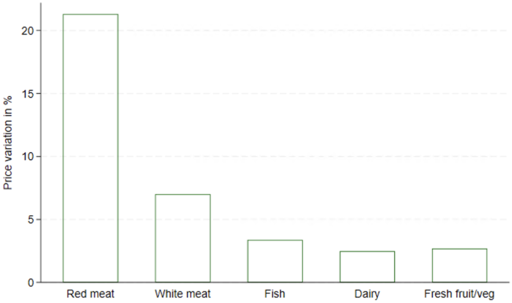


Figure: Bars represent the average price variation post-tax.

Back

Heterogeneous changes across categories and emitters

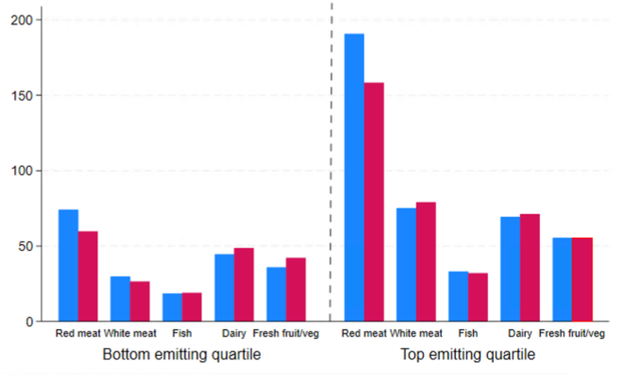


Figure: Emissions per CU before and after tax.
Blue bars indicate before tax emissions and red bars post tax.

▸ Back

Food Carbon Footprints: Contribution

1. Measurement of Carbon Footprints
   - Heterogeneity in carbon footprints across budget items (Pottier, 2022)
   - Need micro-data (Chanut, 2021, André et al., 2024)

   → **Systematic matching: purchase data with environmental data, and households SES**

2. Evaluation of Environmental Policies
   - Public policies to reduce food emissions
     Bonnet et al. (2018), Caillavet et al. (2019), Funke et al. (2022)

   → **Households' reaction while accounting for emission heterogeneity.**

3. Link Food Demand and Environmental Impacts
   - Food as a key adjustment margin (Griffith et al., 2016, Berland and Etilé, 2022)
   - Recessions are good for your health (Ruhm, 2000) ... and for the planet?

   → **Impacts of shocks on households' carbon footprints**

▸ Back