Gender and Carbon Footprints

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Challenges for climate policy acceptance

- Need to curb carbon emissions to attain sustainability goals
- Low support for climate policies needs to be better understood Dechezleprêtre et al. (2022): in high-income countries
  - Support for carbon tax with cash transfers below 35%
  - Support for ban on combustion-engine cars below 45%
- Do differences in emissions explain support for climate policies?
  - No database matches carbon footprints and voters preferences at the individual level
  - Within income heterogeneity explains a large share of household level variation in carbon footprints (Cronin et al., 2019, Douenne, 2020, Berland, 2024)

→ **Gender may significantly influence both the carbon footprints and support for climate policies**

No consensus around the gender emission gap

Data challenges

- Consumption data: household level data - hiding individual level heterogeneity
- Environmental info: average emission intensities - hiding product level heterogeneity

In the literature: positive gap for men, uncertain magnitude

Study	Gender Gap	# of Respondents	Sectors
Carlsson Kanyama et al. (2021)	16% (only for fuel)	620 single adults	All
Rippin et al. (2021)	41%	212	Food
Scarborough et al. (2023)	No gap	55,504	Food
Masset et al. (2014)	24%	1,918	Food

Table: Overview of Studies on Gender Gaps in Environmental and Food Sectors

Study the gender emission gap

French context

- Available individual-level data and detailed environmental info
- Expected high external validity (for high-income countries) given gender norms and support for climate policies comparable to the UK and the US

Food and Transport: 50% of households' total footprint

- Large differences in the carbon intensity across options (modes/goods)
- Habits formed early in life → potentially high welfare loss

Climate policy preferences

- Attitudinal survey to elicit support for policies

What we find

Evidence a 23% gender emission gap

- 20% after controlling for socio-demographics
- Gender emission gap explained by differences in volumes and emission intensities

Study differential support for environmental taxation policies

- Women show stronger environmental concerns
- We do not observe stronger support for climate policies

Outline

Motivation

Data and Method

Gender Emission Gap

Support for Climate Policies

Data sources: individual level consumption

Transportation

- French National Transport Survey, 2019
- **12,569 adults** asked about all their trips for short-distance and long-distance mobility

Food

- INCA3 2017 (French Food Agency)
- **2,000 adults** reporting their detailed daily food consumption

$\rightarrow$ 50% of households' total footprint

Emissions Measurement

$$\underbrace{\text{Emissions}}_{\text{kg CO2 eq}} = \underbrace{\text{Volumes}}_{\text{kg or km}} \times \underbrace{\text{IntensityFactor}}_{\text{kg CO2 eq/kg or kgCO2/km}}$$

Transportation ▸ Intensities per km

- Trip-level emissions from on i) distances ii) mode iii) mode-(vehicle-) specific emission intensity
- Aggregated at individual level

Food ▸ Intensities per kg

- Product-level emissions based on volumes and product intensities ▸ Matching
- Aggregated at individual level

Outline

23% Raw gender gap

Figure: Individual CO2 emissions associated with daily food consumption and transport use by gender

Note: Source: Averages calculated with survey weights.

What can rationalize the gender emission gap?

Socio-demographics

- women could work part-time
- men could be richer

Volumes

- women commute shorter distances
- men should eat more

Intensities

- more red meat for men
- faster car for men

Persists after controlling for socio-demographics

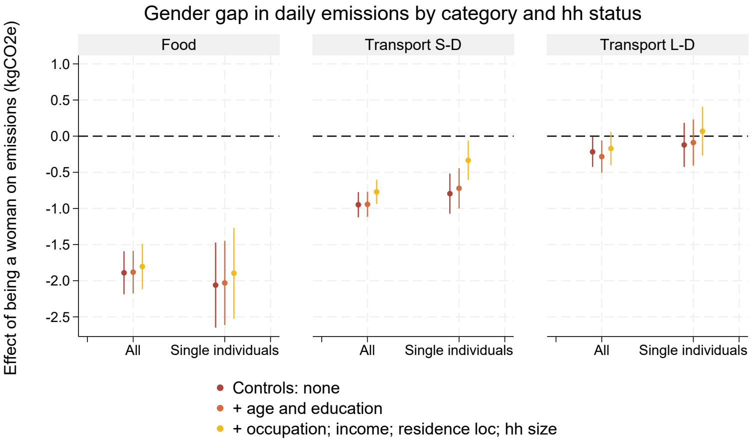

Figure: Estimated gender gap in emissions, women-men

Note: Source: S-D stands for short-distance and L-D for long-distance; hh size stands for household size

Is it just a matter of scale?

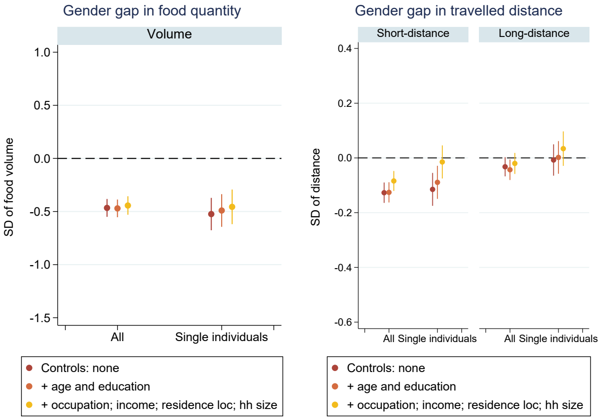

Figure: Scale effect ▸ Calories total

Intensities also explain the gap

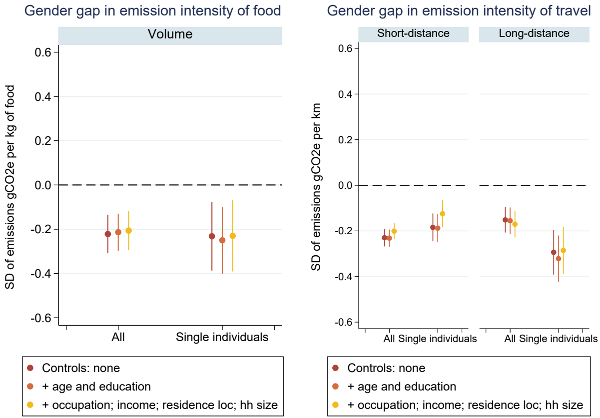

Figure: Emission intensity effect ▸ Calories

Outline

Linking the gender emission gap and support for climate policies

Given the gender emission gap, women should bear a lower burden of climate policies

Does it translate into higher support?

Attitudinal survey data

- Barometer on social representations and climate change (ADEME)
- 7 waves of data (2016 and 2022)
- 10,145 individuals
- Socio-demographics are harmonized with other data sources

Gap might be associated with stronger environmental concerns

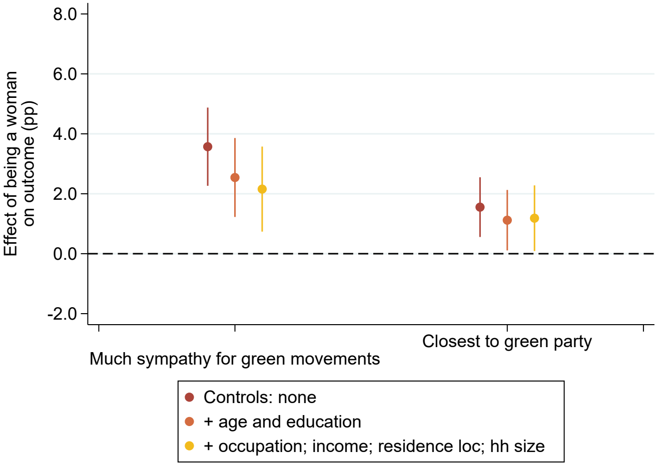

Figure: Gender gap in climate concerns
Note: Survey data from ADEME 2016-2022

But does not imply systematic stronger support for climate policies

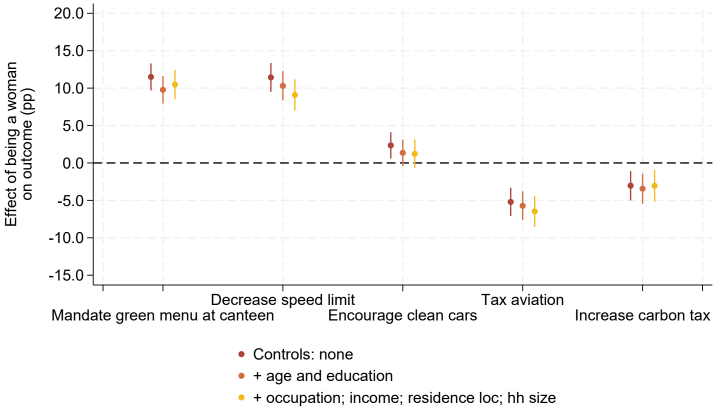

Figure: Gender gap in support for climate policies
Note: Survey data from ADEME 2016-2022

Discussion

Large gender emission gap for food and transport

- 23% (20% after controlling for socio-demographics)
- Gender emission gap explained by differences in volumes and emission intensities

Women show more climate concern

- But no stronger support for climate policies
- Next: Distribution of climate cost policies by gender Method Gap in Scanner data
  - Demand reactions across products categories with heterogeneous intensities
  - Preliminary results: little to no differences in elasticities on top polluting good

References I

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

Carlsson Kanyama, A., Nässén, J., and Benders, R. (2021). Shifting expenditure on food, holidays, and furnishings could lower greenhouse gas emissions by almost 40%. Journal of Industrial Ecology, 25(6):1602–1616.

Cronin, J. A., Fullerton, D., and Sexton, S. (2019). Vertical and horizontal redistributions from a carbon tax and rebate. Journal of the Association of Environmental and Resource Economists, 6(S1):S169–S208.

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

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., and Stantcheva, S. (2022). Fighting Climate Change: International Attitudes Toward Climate Policies. NBER.

Douenne, T. (2020). The vertical and horizontal distributive effects of energy taxes: A case study of a french policy. The Energy Journal, 41(3):231–254.

References II

Galiana, L. and Suarez Castillo, M. (2022). Fuzzy matching on big-data: an illustration with scanner and crowd-sourced nutritional datasets. In Proceedings of the 2022 ACM Conference on Information Technology for Social Good, pages 331–337.

Masset, G., Vieux, F., Verger, E. O., Soler, L.-G., Touazi, D., and Darmon, N. (2014). Reducing energy intake and energy density for a sustainable diet: a study based on self-selected diets in french adults. The American journal of clinical nutrition, 99(6):1460–1469.

Rippin, H. L., Cade, J. E., Berrang-Ford, L., Benton, T. G., Hancock, N., and Greenwood, D. C. (2021). Variations in greenhouse gas emissions of individual diets: Associations between the greenhouse gas emissions and nutrient intake in the united kingdom. Plos one, 16(11):e0259418.

Scarborough, P., Clark, M., Cobiac, L., Papier, K., Knuppel, A., Lynch, J., Harrington, R., Key, T., and Springmann, M. (2023). Vegans, vegetarians, fish-eaters and meat-eaters in the uk show discrepant environmental impacts. Nature Food, 4(7):565–574.

APPENDIX

Fuzzy Matching I

Aim: reduce the distance between text samples

Advantages over supervised ML: flexible matching, no need for training set

- **Definition**: natural language processing (NLP) algorithm projecting text (bags of words) as vectors and computing distances between them.
- **Decision criterion**: maximization of the similarity between vectors

Fuzzy Matching II

Choices:

- "BERT" Language model applied to French Context: 'Camembert'
- Maximise cosine similarity between vectors

[**Disclaimer**: no standard method was found in the literature, Galiana and Suarez Castillo, 2022]

2 steps fuzzy matching with manual checks

1. Matching over product categories (to minimize error)
2. Matching over product (within each product category)
3. 2/3 of products have a score below 0.94 $\rightarrow$ replace by average emission intensity in the product category

Back

Emission intensities: Transport

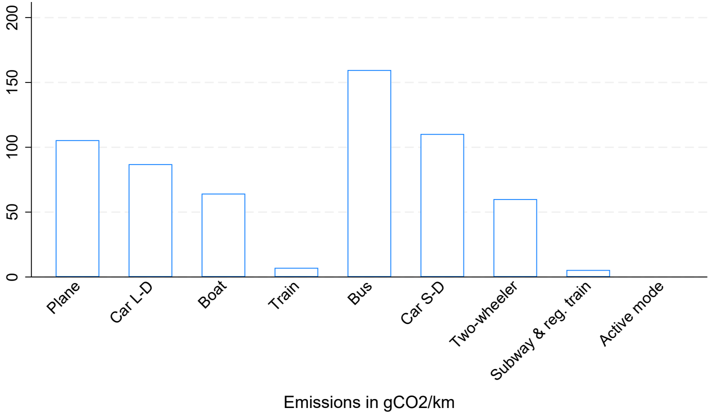

Figure: Emission intensity by transport category (averages)

Note: Emission intensity in gCO2/km.passenger. Difference in average car occupancy rates for short- vs long-distance trips explain differences in intensities ▸ Back

Emission intensities: Food

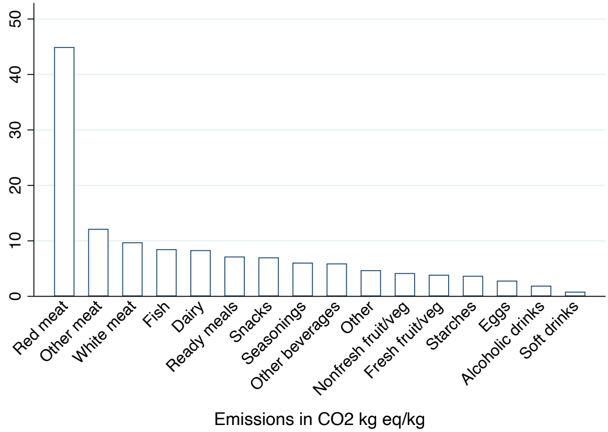

Figure: Emission intensity by food category (averages)

Note: Emission intensity in kg CO_2 eq/kg ▸ Back

Calories

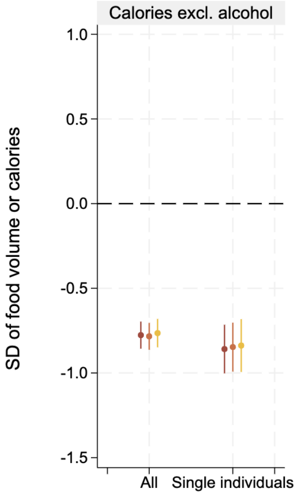

Figure: Calories ▸ Back

Calories

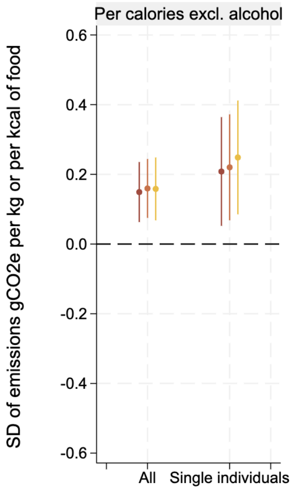

Figure: Emissions per Calorie ▸ Back

Test heterogeneity in reaction to prices change

Study demand reactions across products categories with heterogeneous intensities

- Structural demand model ▸ QAIDS model
- Model inter-categories relations ▸ Identification

→ Compare the estimated budget share elasticities for men and women

Requires data with variation in quantities and price information

- Use household-level scanner data ▸ Detail
- Available for food-at-home (for now)
- Focus on single-adults: robust gender emission gap ▸ Scanner: gender emission gap

▸ Back

Structural Estimation

Almost-ideal demand system model from Deaton and Muellbauer (1980)

Estimated in its **quadratic** version as developed by Banks et al. (1997)

$$s_{ijt} = \sum_{j'} \gamma_{jj'} \ln P_{ij't} + \sum_{r=1}^{2} \beta_{jr} \ln \left(X_{it}\right)^{r} + \Pi Z_{it} + \epsilon_{ijt}$$

Structural Estimation

$$s_{ijt} = \sum_{j'} \gamma_{jj'} \ln P_{ij't} + \sum_{r=1}^{2} \beta_{jr} \ln (X_{it})^{r} + \Pi Z_{it} + \epsilon_{ijt}$$

- household **i**, product category **j**, period **t**
- s_{ijt} expenditure share per product category
- P_{ijt} Price per category
- X_{it} Total food expenses
- Z_{it} Demand shifters
  - Control variables: age, car ownership, education, household size.
  - Regional x Period dummies.

Structural Estimation

$$s_{ijt} = \sum_{j'} \gamma_{jj'} \ln P_{ij't} + \sum_{r=1}^{2} \beta_{jr} \ln \left(X_{it}\right)^{r} + \Pi Z_{it} + \epsilon_{ijt}$$

$\rightarrow$ $\boldsymbol{\gamma_j}$ are price effects, $\boldsymbol{\beta_{jr}}$ capture income effects. Back

Identification

'Observed' Price endogeneity:

- Determinants of prices (quality & local shocks).

→ Leave one out prices per category at the living zone level: $\mathrm{P}_{-\mathrm{it,j}}$

- Identifying assumptions:
  - Within the living zone, at the food category level: retailers do not react strategically to demand shocks.
  - Measurement errors are independent across households within a living zone conditional on the control variables.

Expenses endogeneity:

- Simultaneity between total food expenses & budget shares.
- IV: log-income per consumption unit (Banks et al., 1997). F-stat=82

Back

Income distribution by household type

Variable	Single-Adult		Multi-Adults
	Women	**Men**	
Income (€/month)	1815.92 (1017.82)	2092.13 (1256.84)	3209.09 (1966.55)
Income (€/month/cu)	1741.49 (982.12)	2066.78 (1264.41)	1813.20 (1167.94)

Table: Monthly Income and Income per Consumption Unit

Notes: SD in parenthesis, cu defined following the OECD-modified scale. Kantar 2017-2018.

▸ Back

Scanner Data

Kantar World Panel for France (2017-2018):

- Household-level data → focus on single-adult households
- Food-at-home
- 2k single-adult households (30%) ▸ Income by hh type

▸ Back

Estimation: budget share elasticities

	Women	Men
Estimated Budget share	0.054***	0.060***
	(0.001)	(0.001)
Income elasticity	1.113***	1.466***
	(0.177)	(0.165)
Uncompensated own price elasticity	-1.062***	-0.956***
	(0.081)	(0.042)
Compensated own price elasticity	-1.001***	-0.869***
	(0.087)	(0.046)

Table: Estimates for red meat for women and men.

Back

Gender Emission Gap: Scanner data

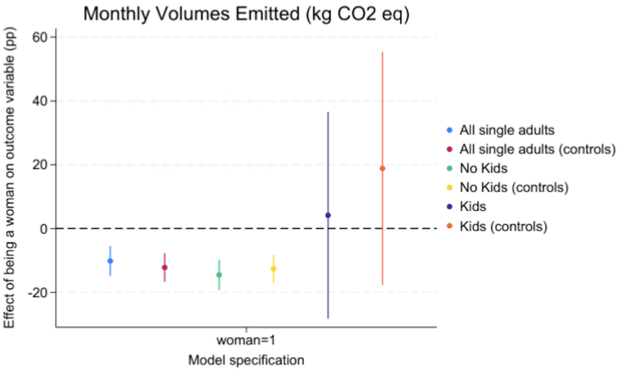

Figure: Emission

Note: Emission intensity in kg CO_2 eq ▸ Back