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The Gender Gap in Carbon Footprints: Determinants and Implications

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Abstract

Understanding the distribution of carbon footprints across population groups is crucial for designing fair and acceptable climate policies. Using granular consumption data from France, we quantify the gender gap in carbon footprints related to food and transport and investigate its underlying drivers. We show that women emit 26% less carbon than men in these two sectors, which together account for half of the average individual carbon footprint. Socioeconomic factors, biological differences and gender differences in distances traveled explain part of the gap, but up to 38% remains unexplained. Red meat and car — high-emission goods often associated with male identity — account for most of the residual, highlighting the role of gender differences in preferences in shaping disparities in carbon footprints.

Keywords: Gender, Carbon Footprints
JEL codes: Q54, Q57

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1 Introduction

Mitigating climate change requires significant changes in consumption patterns (Creutzig et al., 2022), particularly in high-emission sectors such as food and transportation (Intergovernmental Panel on Climate Change (IPCC), 2023). Understanding the distribution of carbon footprints across population groups is essential for identifying key drivers of consumption inequality and for designing equitable environmental policies.[1] While income disparities have been extensively studied in this context, gender remains an underexplored factor despite its well-documented influence on consumption and travel choices.

In this paper, we quantify the gender gap in carbon footprints for food and transport and study its drivers. We use granular and representative consumption data from France matched with detailed environmental information. Food and transport are particularly relevant for at least three reasons. First, taken together, these two sectors account for 50% of household carbon footprints.[2] Second, they offer a wide range of choices with significant variation in carbon intensity — for instance, between transport modes and food products (Poore and Nemecek, 2018; Leroutier and Quirion, 2022). Third, granular environmental impact data exist for both sectors, allowing us to study differences in carbon footprints at an unprecedented fine-grained level: our final dataset includes emission intensity measures varying across more than 2,000 food products and car models.

By using rich individual level data, we are able to assess the importance of different mechanisms that could drive the gap, such as gender differences in employment status, calorie intake, type of food consumed, and to investigate the role of household structure. In doing so, we address the main limitations of the few existing studies that have looked at whether carbon footprints differ by gender. Understanding the mechanisms underlying the gap is key to think about the distributional effects of climate policies.

We begin by quantifying the unconditional gender gap in carbon footprints after having matched survey data recording the food consumption of 2,100 individuals and the transport patterns of 12,500 other individuals to environmental impact data. We find that women's carbon footprints from food and transport consumption are 26% lower than men's on average, with gaps of similar magnitudes in both sectors. As a point of comparison, this gap is of the same magnitude as the difference in food and transport footprints for individuals with below-median household income compared to those with above-median household income.

We then examine the drivers of this gap. First, we find that the gap is only partly driven by gender

[1] Throughout the paper, carbon footprint is defined as the total greenhouse gas emissions caused directly or indirectly by individual consumption. It covers the GHG emissions associated with the consumption of a product throughout its life cycle. For instance, the carbon footprint of food includes emissions from land use (e.g. deforestation) through to the product's distribution. The unit of carbon footprint is in kilogram or ton of CO_2 equivalent emissions, abbreviated tCO_2e.

[2] Sources: for France, cf. Sustainable Development Commission, French Government. Available at: https://www.notre-environnement.gouv.fr/donnees-et-ressources/ressources/publications/article/la-decomposition-de-l-empreinte-carbone-de-la-demande-finale-de-la-france-par, for the US: Song et al., 2019.

differences in socioeconomic characteristics such as education, age, employment status, and household income. After controlling for these factors, the gap decreases to 18%. Second, the gap is not solely the result of a scale effect, whereby men simply eat more (including due to biological differences) and travel longer distances (e.g, due to longer commutes). An Oaxaca-Blinder decomposition reveals that 25% of the food footprint gap and 38% of the transport footprint gap remain unexplained after accounting for socioeconomic differences and differences in calories and distances traveled. Third, we highlight that the residual gender gap is almost entirely explained by the consumption of two goods that are both carbon-intensive and gender stereotypical: red meat and car. These two goods contribute disproportionately to the gap. That is, their contributions to the residual difference in food and transport carbon footprints between men and women — 70% for red meat and 100% for cars — are significantly higher than their shares in the average individual food and transport carbon footprint — 13% for red meat and 84% for cars.[3]

Finally, we compare individuals living in couples to those living alone. We find that the gender gap in transportation is only observed among couples, suggesting a pattern of specialization. The gender gap is particularly pronounced among couples with children. In contrast, the gender gap in food carbon footprints is smaller within dual-adult households relative to single, suggesting convergence: shared meals and joint decision-making may limit the expression of gendered dietary preferences. We highlight the crucial role of household arrangements and intra-household dynamics in shaping the gendered distribution of carbon footprints.

Although our analysis only considers food and transport, back-of-the-envelope calculations suggest that the gender gap in carbon footprints would not disappear if we considered the entire consumption basket instead. Given limited evidence of a significant gender gap in housing emissions, which makes up another 23% of households' emissions, emissions from other goods and services would need to be at least 80% lower for men to fully cancel out the gender gap in food and transport emissions.[4]

Overall, our results shed light on how men and women could be differently impacted by climate policy and on these policies' distributional impacts, particularly in terms of horizontal equity.[5] That women may face a lower mitigation cost could also explain why men are found to be less concerned about climate change than women in high-income countries, including conditional on political ideology: if reducing emissions is more costly for men than for women in these countries, loss aversion and motivated reasoning may make them less concerned with the reality of climate change, in line with the theory set out

[3]While our data does not allow us to separate the influence of gender identity from other factors like environmental concerns, which could also affect demand for red meat and cars, the lack of a gender gap in plane emissions—another high-pollution good less closely associated with male identity—suggests that environmental concerns alone do not fully explain the gender differences.

[4]For example, we may expect clothing to be gender-biased in the opposite direction, but it only makes up 3.5% of household footprints: 270 kilos CO_2e.person in Europe for clothing out of 8 tons CO_2e.person for total yearly consumption. Sources: European Environment Agency https://www.eea.europa.eu/publications/textiles-and-the-environment-the/textiles-and-the-environment-the.

[5]Higher initial carbon footprints do not necessarily imply a higher mitigation cost as measured, for example, by a higher carbon tax incidence; this will, of course, depend on whether mitigation costs differ across genders.

in Bush and Clayton (2023). Moreover, our results have implications for the political economy of climate policy-making, as citizens who are more affected by environmental policy costs and less concerned with climate change are less likely to support mitigation measures. Finally, policies affecting societal norms around gendered consumption patterns, such as associating eating meat with being masculine, could also influence carbon footprints.

Our paper contributes to several strands of the literature. First, we add to the literature quantifying the gender gap in carbon footprints (Osorio et al., 2024; Rippin et al., 2021; Carlsson Kanyama et al., 2021; Masset et al., 2014). To the best of our knowledge, we are the first to investigate the mechanisms underlying the gap. Moreover, most of these studies rely on samples of single individuals from household budget surveys. We show that such estimates may be biased, given the large differences in carbon footprints we observe across different household arrangements. An exception is Osorio et al. (2024), which examines the relationship between the share of females in a household and carbon footprints in Spain, although it does not explore the mechanisms driving this association.

Second, our study adds to the literature on gender differences in economic outcomes such as consumption and earnings. One strand of this literature hasinvestigated the magnitude and determinants of the gender wage gap (Mincer and Polachek, 1974). We apply some of the methods used in that literature, such as the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973), to examine what part of the gender gap in carbon footprints remains unexplained after accounting for socioeconomic differences. Another strand of the social science literature documents gender differences in food consumption (e.g. Rothgerber, 2013; Love and Sulikowski, 2018; Rosenfeld, 2020) and transport behavior (e.g. Scheiner and Holz-Rau, 2012; Motte-Baumvol et al., 2017). These studies propose several explanations for such differences, including men's greater economic and bargaining power due to higher employment levels and earnings, gender specialization in paid versus domestic work and associated trade-offs (Le Barbanchon et al., 2021), and prevailing masculinity norms (Willer et al., 2013; Rothgerber, 2013; Love and Sulikowski, 2018). We add to this literature by quantifying the environmental consequences of these gendered consumption patterns and analyzing their determinants.

Third, we sontribute to the literature examining heterogeneity in carbon footprints along various dimensions, such as income or location. Most of this literature is based on household budget surveys (see, for example, Ivanova and Wood, 2020; Sager, 2019; Cronin et al., 2019; Lyubich, 2025), where most households include both genders, so the gender dimension is typically not investigated. We show that gender is a significant source of heterogeneity in carbon footprints using different data sources. Finally, our study is connected to the literature on the political economy of environmental policies. While this literature has established that women in high-income countries tend to be more concerned about climate change than men (McCright, 2010; Bush and Clayton, 2023), and that the perceived individual cost of climate mitigation is a key driver of environmental policy acceptance (Dechezleprêtre et al., 2025), there is comparatively little evidence on how men and women might face different mitigation costs. While our study does not directly answer this question, understanding gender differences in contributions to carbon footprints is a first step in understanding gender differences in climate policy costs.

The remainder of this paper is structured as follows. Section 2 describes the data and methodology. Section 3 presents the results. Section 4 discusses the implication of our findings.

2 Data and methods

Our analysis relies on two distinct surveys, one on food and the other on transport. They each record consumption quantities on food (respectively transport) for a representative sample of the French population. The method for estimating carbon footprints is similar across surveys and consists in multiplying quantities consumed by emission intensity at the product (respectively transport mode or car model) level. We expect our estimation of carbon footprints based on quantity information to be more reliable than those of studies relying on expenditure data. By focusing on quantities, we avoid conflating consumption volume with price effects (André et al., 2024). Our emission intensity measures reflect the life-cycle greenhouse gas emissions embedded in each final product consumed.

We use the food and transport surveys separately, as they are based on different samples. We sum the gender gaps identified in each sector after harmonizing the data, as explained below. Combining these unlinked datasets implicitly assumes that food and transport carbon footprints are uncorrelated at the individual level. In practice, the correlation between these two domains is unknown, as they reflect distinct consumption behaviors. If, in reality, they are positively correlated — for example, if individuals who consume more meat also tend to drive more — our combined estimates are likely to be conservative.

2.1 Food Carbon Footprints

We use data from the INCA3 survey.[6] It was conducted in 2014-2015 and includes individual food consumption patterns for a representative sample of the French adult population (N=2,121).[7] For each individual we have detailed information on quantities consumed on three representative days for around 2,800 food products, based on a diary (including both food consumed at home and out of home).

This data is matched with food product-level emission intensities from the 2017 (3.0) version of the Agribalyse database produced by the French Energy Agency (ADEME).[8] This dataset includes the environmental impact of 2,480 distinct products consumed in France, spanning raw ingredients to ultra-processed foods. The computation of environmental impacts is based on the Life Cycle Analysis (LCA) methodology and includes impacts from production to consumption: the carbon footprint estimation of

[6] This survey is produced by the French National Health Safety Agency (ANSES).

[7] The survey includes 3,157 adults, but only 2,121 of them have accepted a face-to-face interview and documented their detailed food consumption for at least two days (out of three).

[8] The data is available at https://doc.agribalyse.fr/documentation/utiliser-agribalyse/acces-donnees.

each product takes into account GHG emissions embodied in farming practices, the transport of raw inputs, their transformation and the supply chain.

To match the food consumption data from the INCA3 dataset with environmental data from the Agribalyse dataset, we employed a mixed method involving string matching, Natural Language Processing (NLP), and manual corrections. We first identified perfect matches using string matching and then minimize errors for the most consumed and highest-emission products through manual verification. Systematic matching was performed using a key-terms approach alongside NLP, with a preference for key terms.[9] Ultimately, we successfully matched all the products, with additional hand-checks performed on 14% of them. The full procedure is detailed in Appendix A. Figure B.1 shows the distribution of emission intensities across individual food products. Each bar represents a unique value of greenhouse gas emissions (in kgCO_2e per kilogram of food), sorted in ascending order. Bars are colored by food category, revealing distinct clusters and emphasizing the granularity of the underlying data. This figure illustrates the full spread and variation within the dataset, highlighting that while some categories have tightly grouped values (e.g., fruits and vegetables), others, like meats, span a broader range.

Figure B.2 complements this view by summarizing the average volume weighted emission intensity by food category. Consistent with previous research (Poore and Nemecek, 2018; Clark et al., 2022), animal meats have the highest emission intensities. Red meat, defined as ruminant meat (except for veal), is the highest emitting product, emitting around three times more than the next category, other meat (defined as cold cuts, mix of meats).

2.2 Transport

We use data from the 2019 wave of the French National Transport Survey (EMP), which documents the travel patterns of 13,825 individuals (including 12,569 adults) representative of the French population. Individuals report all the short-distance trips made on a representative day — accounting for their daily mobility —, and all the long-distance trips above 80km made over the past six weeks — accounting for long-distance mobility, including both leisure and business trips.

Trip-level GHG emissions have been estimated by the government department in charge of the data collection, based on information on distances traveled, transport modes, occupancy rate, and the per kilometer emission intensity of each mode in France taken from official sources. For individual vehicles owned by the household — cars, light-duty vehicles and two-wheelers —, the exact emission intensity of the vehicle is retrieved from the exhaustive vehicle registration data via a match at the vehicle license plate level.

Adjustments are made to add upstream emissions from manufacturing, reflect real-world direct emis-

[9] The BERT-based model (CamemBERT) is not specifically trained on food-related vocabulary, which causes all the food products to appear relatively close to each other in the vector space transformation.

sions, and obtain per capita emissions for private modes with several passengers. Compared to the existing literature, this gives much greater precision in trip-level and individual-level emissions. The method is detailed in Appendix A.

Figure B.3 shows the distribution of CO_2 emission intensities across individual car configurations, expressed in grams of CO_2 equivalent per kilometer. Each bar represents a unique value within the total distribution, sorted from lowest to highest. Bars are colored according to the energy type of the vehicle—electric, hybrid, gasoline, diesel, or other—highlighting clusters of low-emission (electric and hybrid) and high-emission (internal combustion) vehicles. This figure emphasizes the granularity of the data and the wide variation in car emission intensity, from less than 100 gCO_2 equivalent per kilometer for hybrid cars against 300 gCO_2 equivalent per kilometer for the highest emitting gasoline cars.

Figure B.4 presents the emission intensity (in gram of CO_2 equivalent (gCO_2e per km per passenger) for various transport modes, distinguishing between short-distance and long-distance travel. For short-distance transport, cars dominate the distribution, emitting 168 gCO_2e per km.passenger, 45% more than the next highest-emitting mode, two-wheeler.[10] Air travel has the highest emissions for long-distance travel, at 174 gCO_2e per km.passenger, making it the most carbon-intensive travel mode. The fact that car and plane have a similar emission intensity before accounting for cars' occupancy rate is consistent with studies from other countries, e.g., Klein and Taconet (2024) on Germany.

This breakdown highlights how private vehicles and air travel contribute disproportionately to emissions compared to public and active modes of transport.

2.3 Harmonizing the data

We harmonize individual-level food carbon footprints, carbon footprints from short-distance travel and from long-distance travel to reflect annual carbon footprints per capita for the same population groups.[11] Table B.1 presents the main sociodemographic characteristics, comparing the food and transport surveys. In terms of gender distribution, 58% of the food survey participants and 55% of the transport survey participants are female.[12] Average household size and work status are similar across samples. The transport survey has slightly older and less educated individuals than the food survey. In section 3.1, we apply survey weights to calculate average carbon footprints by gender to obtain results representative at the national level.

[10]The lower per passenger emission intensity for long-distance trips by car is due to the higher occupancy rate for long vs short-distance car trips.

[11]In particular, we drop individuals aged 80 and more in the transport data since the food survey only interviews individuals below 79. We convert the food and short-distance travel daily carbon footprints to annual carbon footprints by multiplying by 365. Finally, we convert the long-distance travel carbon footprints expressed as 6-week-long carbon footprints to annual carbon footprints by multiplying by 8.67 (52/6=8.67).

[12]In the survey, the question about sex, not gender; in the absence of data on gender, we assign to each survey respondent the gender corresponding to the sex variable.

Reassuringly, the average individual carbon footprints that we obtain for each category is consistent with per capita carbon footprints estimated with a top-down approach combining data on sectoral GHG emissions, trade and input-output tables. Our average individual has annual food carbon footprints of 1.9tCO_2e and annual transport carbon footprints of 2.7tCO_2e. In 2017, the top-down approach estimation gives per capita food carbon footprints of 2.1tCO_2e and per capita transport carbon footprints of 2.8tCO_2e (Baude, 2022). For food, our results are also consistent with Barbier et al. (2019)'s paper using individual-level food consumption data, reporting 2tCO_2e.

We also harmonize the control variables used to estimate conditional gender gaps across the two datasets. In section 3.2, we run multivariate OLS regression of the form:

$$Y_i = \beta_0 + \beta_1 Female_i + \beta_2 X_i + \mu_i \tag{1}$$

Y_i is the outcome of interest for individual i, such as her carbon footprint from transport, $Female_i$ is a dummy variable for individual i reporting a female gender, β_1 is our coefficient of interest measuring the effect of being female on the outcome, and X_i is a vector of socioeconomic, demographic and location controls observed at the individual or household level. μ_i is the error term.

In several figures, we progressively add more control variables. In the most basic regression ("Controls: survey wave"), we control for the time of year when the survey is conducted. The variables slightly differ between the food and transport surveys: for the food survey, we use indicators for the four seasons, while for the transport survey, we include the day of the week and two-month sampling periods (e.g., May-June 2018 until March-April 2019).[13] In the "+sociodemographics" regression, we additionally control for age, education, and household size.[14] In the "+location" regression, we add controls for urban unit size with indicators for the size of the residence's urban area.[15] The "+household income" regression further includes categories of household net income (after transfers but before income tax).[16] Finally, the "+employment status and professional category" (also referred to as "all controls") regression adds indicators for the socio-professional category, and a dummy for whether the person is in employment.[17] For the subsample of individuals in employment, we can further include controls related to the type of employment contract and characteristics, that are known to differ between men and women and likely influence carbon footprints: a dummy variable for working part-time – which is more common among women, and, for the transport survey only, a continuous measure of commuting distance – which is longer

[13] The food survey includes four seasonal indicators: Winter, Spring, Summer, and Fall, while the transport survey uses seven day-of-week and six bi-monthly indicators.

[14] The age categories are 18-44, 45-64, and 65-79 years. Education levels include less than secondary or vocational degree, end of high school diploma, higher education degree $\leq$ 2 years, and higher education degree $>$ 2 years. Household size is included as a linear control.

[15] The categories are: less than 2,000 inhabitants, 2,000-19,000 inhabitants, 20,000-99,000 inhabitants, more than 100,000 inhabitants outside the Paris area, and the Paris area.

[16] For the food survey, the net income categories range from $<$690€ to 4600€ per month, with 10 categories. The transport survey uses categories of household income deciles per consumption unit based on the national income distribution.

[17] Socio-professional categories mix activity status and type of occupation for the active individuals, with the following categories: student, pensioner, other inactive, blue-collar low-skilled, white-collar low-skilled, intermediate occupations, white-collar high-skilled and craftspeople and shopkeepers.

for men – and a dummy variable for whether the individual works night shifts.

3 Results

3.1 The unconditional gap in carbon footprints

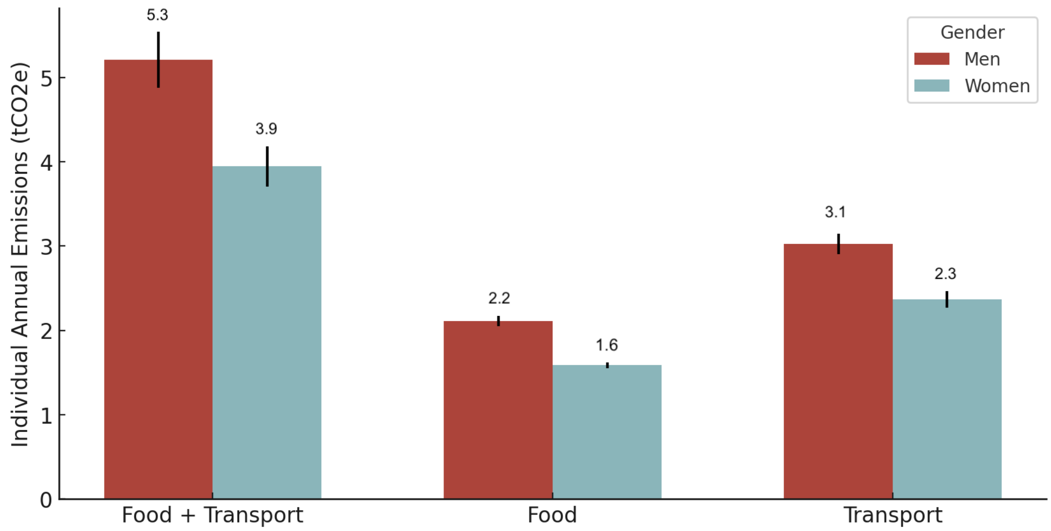
Figure 1 shows the average carbon footprints by gender and consumption category. The annual carbon footprints associated with men's food and transport consumption are 5.3 tCO_2e on average, while that associated with women's food and transport consumption is 3.9 tCO_2e, 26% lower. The gap is driven by differences in both food and transport.

Figures B.5, B.6, B.7 present the distributions of annual food and transport carbon footprints by gender. We separate short-distance and long-distance travel to study their distributions but group them together for the rest of the analysis. For food, the distribution for women is slightly skewed to the right, whereas for men, there are clear outliers, individuals in the top 1% of carbon footprints emit around 12 tons of CO_2 annually—approximately four times the average. Nevertheless, the gender gap persists even after excluding these outliers. When excluding the top and bottom 1% the gender gap in food carbon footprints decreases marginally to 24%. It is 16% when the top and bottom 5% are excluded.

Distributions of short-distance transport carbon footprints have the same highly skewed shape across genders, with values for men consistently higher. 20% of men and 23% of women have zero emissions from transport, mostly because they use non-emitting modes of transport. For long-distance travel, around 60% of individuals record zero emissions because they haven't done any long-distance trip, which is partly due to the way data is collected: only the long-distance trips done in the six weeks before the interview are recorded. The distributions are again highly skewed to the right, with men showing slightly higher values.

Figures B.9 and B.8 present the decomposition of food consumption and travel into two categories: food consumed at home versus out-of-home and work-related versus non-work-related travel, separately for short-distance and long-distance travel. The gender gap in food carbon footprints is larger for food away from home (50%) compared to food consumed at home (25%). For travel, the gap is driven mostly by differences in work-related travel. The smaller gender gap in carbon footprints for food consumed at home and leisure-related travel may be influenced by joint household decisions, which reduce the gap in food consumption at home (convergence) but increase it for work activities (specialization). These patterns are further explored in the following subsections.

Figure 1: Individual Yearly Food and Transport Carbon Footprints by Gender.



Notes: Source: Food consumption: INCA3 (N=2,121); transport: EMP (N=12,077). Averages calculated with survey weights. The dark vertical bars indicate 95% confidence intervals.

3.2 Does the gap persist conditional on socioeconomic characteristics?

A vast literature in social sciences documents gender differences in economic conditions, labor market integration, domestic labor, and leisure activities (see Blau and Kahn, 2017, for review on the gender wage gap). We investigate what share of the gender gap in carbon footprints could be explained by these differences by restricting the sample to individuals in employment and controlling for various sociodemographic characteristics.

One important difference between men and women is the lower labor force participation of women, which can influence dietary requirements and demand for mobility.[18] Work-related mobility is partly constrained, and work trips outside of commuting could be considered production-based rather than consumption-based emissions. Therefore, it is important to understand how much the gap is explained by work-related mobility. On the one hand, work-related trips – which include both commuting and other business-related trips – explain most of the gender gap in transport carbon footprints, as can be seen in Figure B.8. On the other hand, the gap is not only driven by an extensive margin effect where women are simply less likely to be employed and do not need to commute: restricting the sample to the employed in Figure B.10, we find a gender gap in carbon footprints as large as for the general population, of 26%. Differences in the scale and intensity of work-related trips must also contribute to the gap.

To understand the role of other characteristics, we run multivariate regressions and try to “kill the gap” by adding more and more controls. Figure 2 shows the results. The overall gap decreases from 26%

[18]In 2016, 67.6% of women aged 15-64 in France participated in the labor market, compared to 75.4% of men. Source: French National Statistical Institute (INSEE).

to 18% when we control for household size, household income, city size, and individual's age, education, employment status and socio-professional categories. However, the 95% confidence intervals overlap, so we cannot rule out that the conditional and unconditional gaps are equal.

The gender gap in the carbon footprints of food is barely affected by the addition of controls and decreases from 28% to 22%. The gender gap in transport decreases from 25% to 15% after controlling for city size of the place of residence, household income, individual employment status, and socio-professional categories. Thus, the gap comes partly from a composition effect: women are more likely to live in large cities and poorer households and are more often unemployed or outside the labor force, all characteristics associated with lower carbon footprints. The transport survey includes additional useful control variables that are not available in the food survey. Figure B.12 shows that the gap in transport emissions decreases but does not close when we also control for more detailed characteristics that influence carbon footprints and are correlated with gender, namely more detailed socio-professional categories,[19] category of household,[20] ability to drive and being in a household that owns more than one car.

Since we do not observe individual wages, one might argue that the gender gap in carbon footprints simply reflects the gender wage gap, as both have a similar magnitude (Palladino et al., 2025).[21] However, if income were the main driver, we would expect single men—who earn more on average—to still have higher transport carbon footprints than single women. In section 3.5, we show that instead, the gender gap in carbon footprints is not significant anymore in the subsample of singles once we condition on socioeconomic characteristics – including when we only control for socioeconomic characteristics other than income. This suggests that household structure and specialization in couples play a key role in shaping transport carbon footprints rather than income alone.

To assess the extent to which sociodemographic differences explain the gender gap in carbon footprints, we analyze how much of the mean difference between men and women can be attributed to observable characteristics. We follow the Oaxaca-Blinder (O-B) decomposition method, commonly used in labor economics, to distinguish between explained and unexplained components (Oaxaca, 1973; Blinder, 1973). Unlike standard OLS regressions, which assume a single relationship between explanatory variables and carbon footprints between gender groups, Oaxaca-Blinder allows for group-specific coefficients, accounting for potential differences in consumption patterns or systematic behavioral differences between groups. This approach decomposes the observed gap into two parts: one driven by differences in characteristics (the endowment effect) and the other by differences in coefficients (the structural or unexplained effect), which may reflect behavioral differences, social norms, or unobserved preferences. Table B.2 presents results from a twofold Oaxaca-Blinder decomposition. In the food sector, we find that 92% of the gender gap remains unexplained after controlling for sociodemographics, location, household income,

[19] Instead of five main occupation categories, we have 42 categories mixing activity status (e.g., student or inactive outside the retired), detailed occupation category (30 categories) for the employed and unemployed, and broad occupation category for the retired.

[20] With five categories: single, single parent, couple without children, couple with at least one child, and complex family.

[21] In 2018, the gap in gross hourly wage adjusted for differences between occupations and firms was 15% according to Palladino et al. (2025).

employment status, and socio-professional category (column 1). For transportation, the unexplained share of the gender gap is 69% (column 4).

Could gender differences in employment and occupation characteristics, as documented in the labor literature, explain part of the remaining gap, conditional on being employed ? For example, Le Barbanchon et al. (2021) and Frändberg and Vilhelmson (2011) find a significant gender gap in willingness to commute longer distances and actual commuting distances, and link it with the gendered division of labor and domestic work. Work-related emissions indeed play a key role in the transport gap in carbon footprints: Figure B.13 shows that the gender gap only exists for work-related emissions – including both commuting trips and other business-related trips – but not for leisure emissions. We take advantage of detailed covariates on employment characteristics in the food, and even more the transport surveys, to investigate the role of employment characteristics in each gap for the subsample of employed individuals.

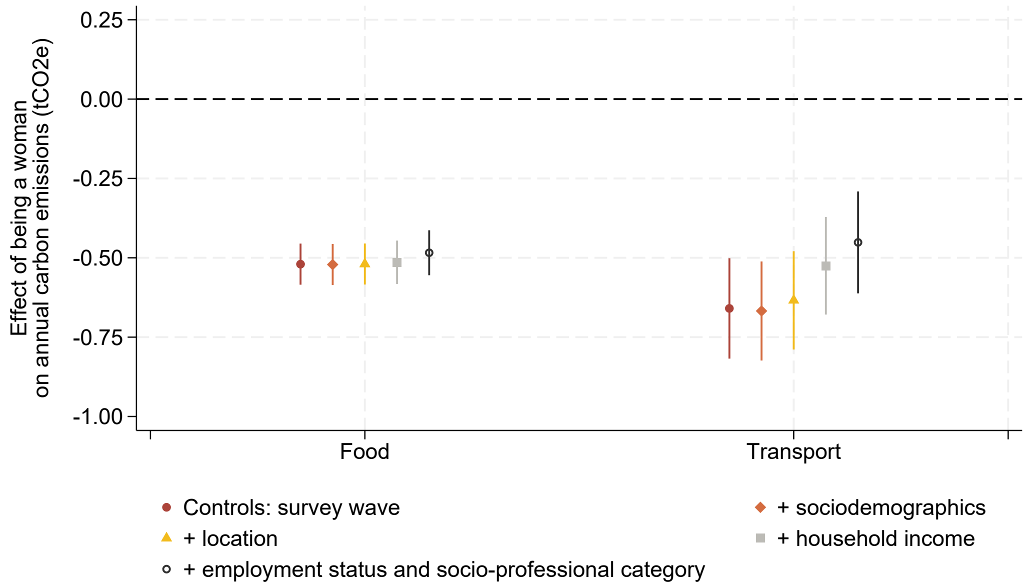
In Figure B.11, we replicate the multivariate analysis from Figure 2, with one modification: instead of controlling for employment status, we control for three employment characteristics—part-time work, night shift work, and, for transport only, commuting distance. The gap decreases from 26% to 18%, the same magnitude as for the full sample, primarily due to a reduction in the gender gap in transport carbon footprints. This finding allows us to rule out employment characteristics—particularly differences in commuting distances—as the sole explanation for the gap. The remaining gap could be attributed to differences in the amount and carbon intensity of business-related trips outside commuting, as well as variations in the carbon intensity of commuting itself. One potential concern with work-related trips outside commuting is whether they should be considered part of men's consumption-based carbon footprint, given their connection to the production process. However, Figure B.14 shows that the gender gap in transport carbon footprints persists among the employed, even when emissions from work-related trips outside commuting are excluded. This suggests that the gap is driven by differences in the carbon intensity of men's trips, including those related to commuting.

3.3 Biological differences: is it just that men eat more?

Men's dietary guidelines differ significantly from those for women. For example, both the French Health Agency (ANSES) and the USDA recommend that women consume, on average, around 21% fewer calories than men.[22] In our data, the difference in calorie intake is 10% greater than the biological recommendation would suggest.. This excess gap in calorie intake is mainly driven by men having more calories from alcohol

[22] The USDA Dietary Guidelines for Americans (2020–2025) indicate the following calorie requirements: men aged 18–44, 2,400–3,000 calories, and for women, 2,000–2,400 calories; for men aged 45–64, 2,200–2,800 calories, and for women, 1,600–2,200 calories; and for men aged 65–79, 2,000–2,600 calories, and for women, 1,600–2,000 calories. For each group, we take the midpoint of these ranges. The French guidelines are similar in terms of recommended daily calorie intake. For example, France's 2016 guidelines suggest 2,600 kcal per day for adult men aged 18–69 and 2,100 kcal for adult women aged 18–59, which aligns closely with the midpoints of the USDA's more detailed ranges for similar age groups. We use the US guidelines in this analysis because they provide more specific recommendations by age group, allowing for finer distinctions in the data.

Figure 2: Conditional Gender Gap in Food and Transport Carbon Footprint, Full Sample.



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "+ sociodemographics" additionally controls for age, education and household size. "+location" additionally controls for size of the urban unit of residence. "+household income" additionally controls for household income. "+employment status and professional category" additionally controls for employment status and socio-professional category. Source: Food consumption: INCA3 (N=2,121); transport: EMP (N=12,077)

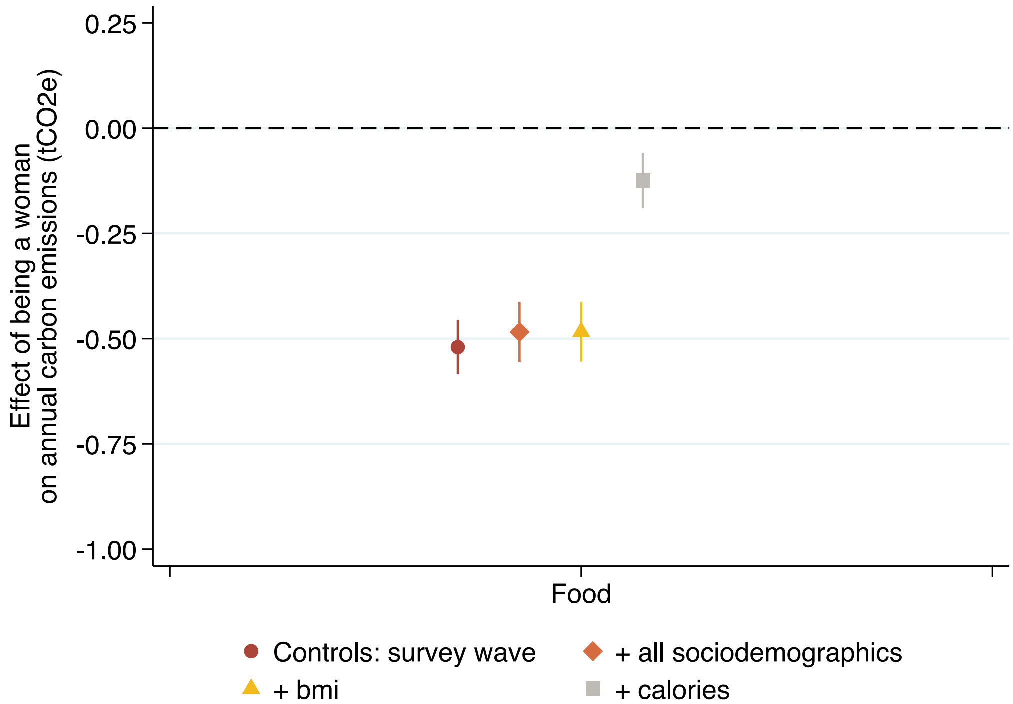
consumption, which are not included in the dietary guidelines. This suggests that part of the gender gap in carbon footprints is due to a difference in food volumes that is not explained by biological differences.

Since calorie requirements differ from actual calorie intake — particularly as they are general guidelines and do not account for alcohol consumption — we also directly control for calorie intake in our regressions. While calorie intake is partly driven by individual food choices and thus may be endogenous, it remains an informative control to isolate the role of food volume in emissions. Ideally, one might control for recommended caloric intake to capture biological needs. However, because recommended intake is entirely determined by gender and age, it is perfectly collinear with our existing sociodemographic controls, making it infeasible to include directly in the regression. We therefore rely on actual calorie intake—including alcohol—to capture individual-level differences in energy consumption.

Figure 3 presents the results from the specification shown in Figure 2, now including controls for BMI and individual calorie intake estimated based on the food diaries. Controlling for BMI results does not change the estimated coefficient relative to the specification that includes all sociodemographic controls.[23] In contrast, controlling for calorie intake significantly alters the results: the gender gap in

[23]Controlling for BMI allows us to account for individual differences in body size, which may influence both food intake and dietary composition. While men and women have similar average BMI in our sample, BMI still captures relevant

Figure 3: Gender Gap in Food Carbon Footprints, the Role of Differences in Dietary Requirements



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "+ all sociodemographics" additionally controls for age, education and household size, location, household income, employment status and socio-professional category, "+ BMI" additionally controls for BMI and "+ calories" additionally controls for the calories consumed, including alcohol. Source: Food consumption: INCA3 (N=2,121).

food-related carbon footprints shifts from -0.48 tCO_2e to -0.12 tCO_2e. Although the 22% gender gap in food emissions is numerically similar to the 21% difference in recommended calorie intake, this does not imply that the gap is fully explained by biological needs. First, actual calorie intake in our data exceeds recommended values, especially for men, due in part to alcohol. Second, after controlling for calorie intake and sociodemographic factors (as shown in Table B.2 column 2), an unexplained difference of 6.5% remains, which accounts for 25% of the original gender gap in food carbon footprints. This suggests that the remaining disparity is likely driven by systematic differences in consumption habits, particularly men's higher consumption of high-emission-intensive goods.

3.4 Contributions of red meat and car to the gender gap

The social science literature emphasizes the connection between red meat consumption and male identity (Rothgerber, 2013), and car and male identity (Scheiner and Holz-Rau, 2012). For instance, while car is

within-gender variation, which could otherwise confound the analysis.

not the focus of the paper, Cuevas et al. (2021) have many car-related items in its 500 Most Masculine Interests retrieved with a singular value decomposition method based on interests reported on Facebook; Willer et al. (2013) find that random feedback suggesting men are feminine makes them more interested in buying an SUV, among others; Rothgerber (2013) find that men believe more than women that eating meat is normal for humans. Building on this literature, we investigate the specific contribution of these two products to the gender gap in carbon footprints. Red meat is by far the most carbon-intensive food product (see Figure B.2), while both car and plane are the most carbon-intensive transport modes (see Figure B.4).

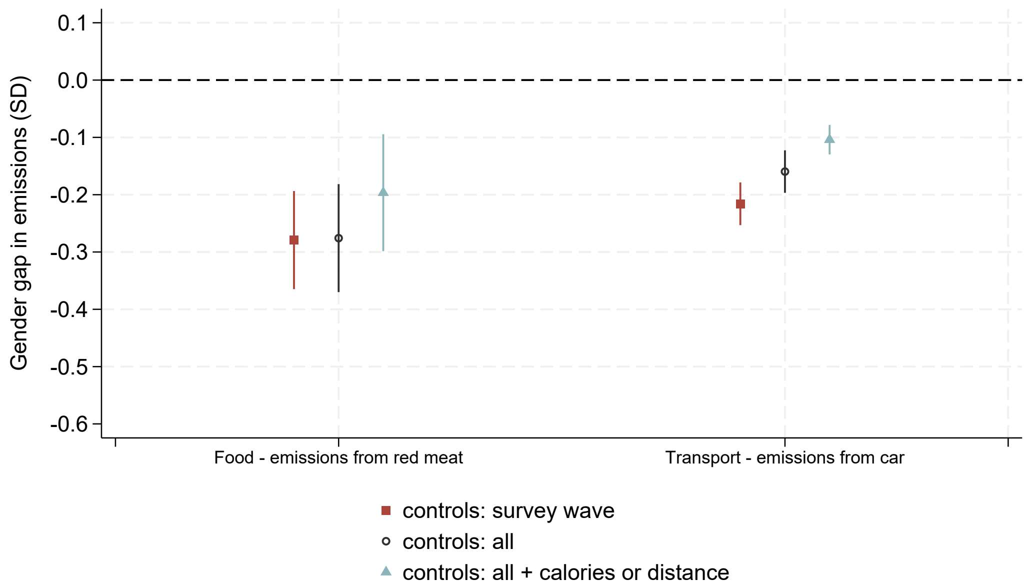
Figure 4 shows the conditional gender gap in carbon footprints coming specifically from red meat and car, using normalized carbon footprints to ease comparison. Both with basic and with the full set of sociodemographic controls, women's red meat emissions are 0.28 SD lower than men's. Their car emissions are 0.22 SD lower with basic controls and 0.16 SD lower with the full set of controls. Even controlling for daily calorie intake for food, and for total distances traveled for transport, there remains a substantial gap: higher red meat consumption and car emissions are not only driven by higher calorie requirements and the need to travel longer distances due to constrained work trips and longer commutes, as highlighted in Le Barbanchon et al. 2021; Frändberg and Vilhelmson 2011.

Another way to highlight the contribution of red meat and cars to the gender gap in carbon footprints is to contrast their share in emissions for the average person in the data and their share in the emission gap. Red meat GHG emissions make up only 13% of total food carbon footprints, while car emissions make up 84% of total transport carbon footprints on average. We estimate the contribution of red meat to the food gender gap by dividing the estimated coefficient on the gender dummy in the regression of red meat emissions by the corresponding coefficient in the regression of total carbon footprints. We do so for the three different regressions of Figure 4: the one with survey wave controls, the one with all sociodemographic controls, and the one controlling for calories (for food) or distance (for transport).

Figure B.15 shows that while red meat contributes to 13% of emissions in the average person's diet, the gap in red meat emissions explains 25% of the emission food gap using basic controls, and 70% when we control for all socio-demographics and calories. Thus, the gender gap in red meat consumption disproportionately impacts the gender gap in carbon footprints for food. The same holds true for car emissions for transport: Figure B.16 shows that car represent 84% of an average person's transport footprint, but the gender difference in car emissions explains 93% of the gender gap in transport emissions, and 100% when all socioeconomic characteristics are controlled for. By contrast, there is no significant gender gap in plane emissions, the other high-polluting transport mode, as shown in Figure B.17.

What explains this gap in car emissions? In contrast to red meat, which is a significantly larger share of men's food volume compared to women, we do not find that men use a car more often as a proportion of distances traveled in Figure B.20, once socioeconomic factors are controlled for. Instead, the contribution of car emissions to the gender transportation gap comes from the fact that men travel longer distances than women overall (distance gap), and when they do use the car, their car trips have a

Figure 4: Food: Gender Gap in Red Meat and Car emissions



Notes: The point estimates and 95% confidence intervals in red show the estimated coefficient for the gender dummy "female" from separate OLS regressions of standardized emissions from red meat consumption and standardized emissions from car trips. The point estimates and 95% confidence intervals in blue show the estimated coefficient for the gender dummy "female". "Controls: survey wave" only controls for the time of year when the survey is conducted "controls: all" additionally controls for age, education, household size, size of the urban unit of residence, household income and employment status and socio-professional category. "Controls: all + calories or distance" additionally controls for reported daily calorie intake for the regression on food and for reported total distances traveled for the regression on transport. Source: INCA3 (N=2,121); EMP (N=12,077)

higher emission intensity: this is because men's car trips have a lower occupancy rate and are done in a more carbon-intensive car.

An Oaxaca-Blinder decomposition reveals that when accounting for the distance traveled by individual and sociodemographic factors (Table B.2 column 4), an unexplained difference of 38% of the gender gap in transport carbon footprints remains. Figure B.18 shows this gender gap in distance, in the inverse of occupancy rate[24], and in the emission factor of single individuals' car — the only category where the choice of the car owned by the household can be assigned to one gender. The inverse occupancy rate in women's car trips for short-distance travel is 0.20 SD lower on average than in men's car trips, and single women own cars that are, on average, 0.11-0.14 SD less carbon-intensive than the cars owned by men.

[24]One divided by the number of people in the car, which takes a maximum value of 1 if the person is solo-driving for all their car trips

3.5 Heterogeneity by household type: couples vs singles

Figure B.19 shows the unconditional gap by household type, separately for single individuals, couples without children and couples with children.[25] Both single men and single women have lower carbon footprints on average than those living in dual-adult households and than the overall sample: single men have an annual footprint of 4.7 tCO_2e, and single women have an annual footprint of 3.6 tCO_2e. The gender gap in carbon footprints is slightly smaller for them than for the main sample of analysis, at 23%.

In Figure 5, we show the gap after adding all the sociodemographic controls. These results are suggestive of specialization within the household in transportation patterns. The gender gap in transportation carbon footprints is much larger for couples than for singles, where the gap is not significantly different from zero. This gap is particularly pronounced for couples with children (-0.85tCO_2e, compared to -0.47 tCO_2e for couples without children), likely due to women with children working closer to their homes. This result is consistent with research on family labor supply and time allocation, which suggests that couples with children often make trade-offs between commuting time and childcare responsibilities (Blundell et al., 2018), and that the gender gap in willingness to commute is strongest for married women with children and lowest for single women without children (Le Barbanchon et al., 2021).

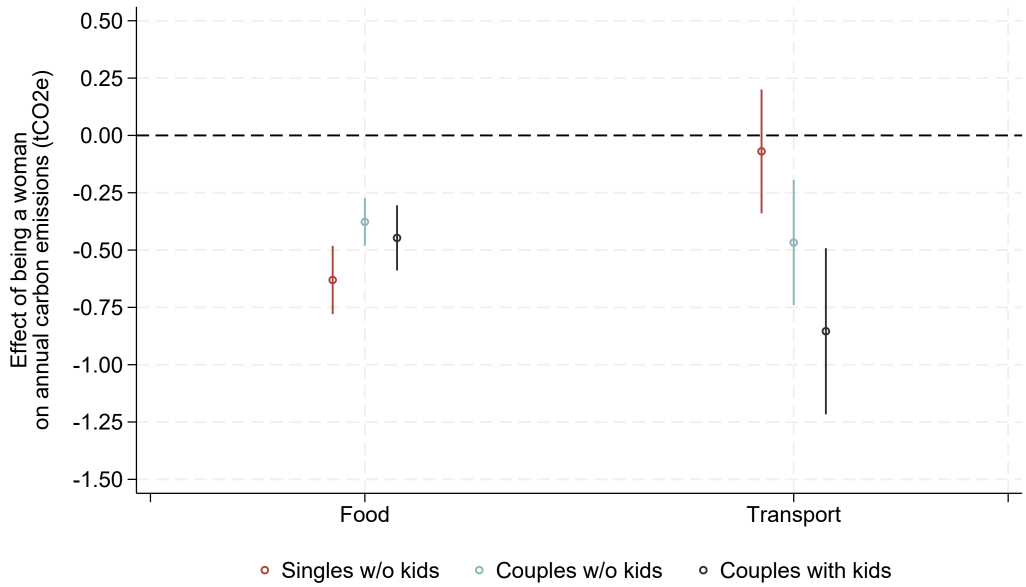
In contrast, the gender gap in food carbon footprints is smaller for dual adult households (-0.37 tCO_2e for couples without children and -0.47 tCO_2e for couples with children) than for singles (-0.62 tCO_2e). This decreasing gap is suggestive of convergence in consumption patterns. This is consistent with the food studies literature, which demonstrates that couples often adjust their food choices to accommodate each other's preferences (Bove et al., 2003). Adjusted predictions from regression models provide additional insight: women's average carbon footprints from food increase substantially when moving from singlehood (1.53 tCO_2e) to cohabiting relationships without kids (1.69 tCO_2e), whereas men's carbon footprints remain relatively stable (2.16 tCO_2e for singles, 2.14 tCO_2e for couples without kids). This suggests that convergence within couples is primarily driven by women increasing their carbon-intensive food consumption, likely eating more meat, rather than men reducing theirs. This pattern is in line with existing research, which finds that dietary adjustment within households is often asymmetrical, with women more likely to align their eating habits to those of their male partners (Brown and Miller, 2002; Sobal, 2005; Gregson and Piazza, 2023).

These convergence and specialization patterns are also visible for red meat emissions and car emissions specifically. Figure B.21 shows that the gender gap for red meat emissions is larger for singles than for the overall sample (shown in Figure 4), while the gender gap in car emissions is smaller – yet still significant, compared to the gap for total transport in carbon footprints.

While our findings support much of the existing literature on the existence and direction of the gender gap in carbon footprint, we also highlight potential biases in studies that focus solely on single

[25] We exclude single-adult households with children from the analysis because the sample of single men with children is very small (only 16 men in the total sample of 667 single in the food survey).

Figure 5: Conditional Gender Gap in Carbon Footprints by Household Type, Full set of Controls.



Notes: The point estimates and 95% confidence intervals in red show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, controlling for the variables listed thereafter, for the subsample of single adults without kids. The point estimates, and confidence intervals in blue and black show the corresponding coefficients for the subsample of individuals living in a couple without kids and individuals living in a couple with kids, respectively. Control variables include the time of year when the survey is conducted, age, education, household size (not for singles), size of the urban unit of residence, household income, individual employment status and socio-professional category. Source: Food consumption: INCA3 (singles without children: N=584; couples without children: N=800; couples with children: N=654); transport: EMP (singles without children: N=3,629; couples without children: N=3,820; couples with children: N=3,917).

adult households. Our findings suggest that studies focusing solely on single individuals to estimate the gender gap in carbon footprints probably overestimate the food carbon footprints gap and underestimate the transport carbon footprints gap, as bargaining power within the household and gender norms likely influence these outcomes in dual-adult households.

4 Implications of the gender gap in carbon footprints

4.1 Putting our results in perspective

To put the magnitude of our findings in perspective, we calculate the income gap in carbon footprints for the same consumption categories, given that differences in carbon footprints by income level have received a lot of attention in the literature (Chancel, 2022; Sager, 2019). We first partition the samples into two equal-sized groups to mirror the partition by gender. We obtain an unconditional income carbon footprints gap of the same magnitude as the gender carbon footprints gap, 27%, driven by the gap in transport carbon footprints. If we instead compare more extreme income categories, the top and bottom income quintiles, excluding the middle 60% of the income distribution, we obtain an income carbon footprints gap of 46%, only 1.8 times larger than the difference between men and women. Arguably, the income gap could be larger for other consumption categories, including less essential goods than food and transport. Still, the relatively high magnitude of the gender carbon footprints gap compared to the income carbon footprints gap suggests that gender would warrant more consideration as a relevant dimension of carbon inequality.

Another way to view this gap is by asking how much French carbon footprints would decrease if all men adopted the average carbon intensity of women observed in our sample for food and transport, holding quantities consumed constant (calorie requirements for food and observed distances for transport). We find that if all adult men adopted the same carbon intensity of consumption as adult women, without affecting women's consumption, food carbon footprints would decrease by 1.9 $MtCO_2e$ and transport carbon footprints by 11.5 $MtCO_2e$ in France. These amounts correspond to threefold the annual emission reductions expected from the agriculture and transport sectors to comply with French climate targets by 2030 (Haut Conseil pour le Climat, 2024).[26] This scenario is, of course, not fully realistic given that carbon intensity partly depends on quantities consumed, in particular for transport (distances traveled). It still provides a useful benchmark that we can compare to emission reductions achieved by flagship climate measures in these sectors.

One limit of our study is to only consider food and transport, out of all consumption categories. Would the gender gap in total carbon footprints disappear or even reverse if we could observe individual carbon footprints for other consumption categories? Evidence from the literature suggests that this is unlikely to be the case. In France, transport and food contribute to 30% and 22% of per capita footprint, respectively (Baude, 2022). The remaining 48% includes housing (23%), tangible goods (10%), the reallocation of emissions from final government consumption (8%), and other services (8%). For government consumption, the dominant approach in the literature is to allocate equal emissions to each individual. So the gender gap in carbon footprints would only disappear if women emitted significantly more than men in their housing, durable goods and service consumption. Housing emissions are hard to assign within the household, so the only proxy we have on gender gaps is for singles: a study in four European countries reports unconditional gender gaps in housing energy consumption between -4% and +4% depending on the country (Räty and Carlsson-Kanyama, 2010). Assuming that the gap for France lies in this interval, that men and women have a similar carbon intensity for housing energy, and that singles are representative of the overall population, this gives a housing footprint gap of at most -4% with lower carbon footprints for men. The gap for tangible goods and other services would then need to be at least -80% to fully cancel out the gap in food and transport, which is unlikely.

[26]France's emission reduction targets are for domestic emissions, whose scope differs from our consumption-based approach of quantifying emissions which include imported emissions.

4.2 Policy implications

Our findings have several implications for climate policy. First, they suggest that the burden of carbon taxation in the food and transport sector could be greater for men than for women, assuming that both genders have the same tax elasticity. Most evidence on the distributional effects of carbon taxation focuses on income (vertical equity considerations), and the papers investigating horizontal equity rely on household-level expenditure data and are not able to identify the effect of gender. Estimating the incidence of a carbon tax across gender groups using individual-level consumption data is an interesting avenue for future research, particularly given our findings on the gender differences in carbon footprints. However, this would require access to price information, which the data used in this study does not include.

Understanding the intersection of gendered consumption patterns and climate concerns is critical because the perceived costs of climate policy—especially those impacting household budgets—strongly influence policy support (Dechezleprêtre et al., 2025). Our findings suggest that women who have lower carbon footprints may be more likely to support climate policies than men. To the extent that our findings are partly explained by gendered preferences for some carbon-intensive goods, support for climate policy affecting the cost of these goods could become polarized across gender lines.

The gender gap in carbon footprints can also be linked to previously documented gender gaps in climate-related attitudes and behaviors, such as climate concerns, climate-friendly actions, and leadership (McCright, 2010; Bush and Clayton, 2023; Elert and Lundin, 2022; Mavisakalyan and Tarverdi, 2019; Bandyopadhyay et al., 2023). Women's higher levels of concern about climate change (Bush and Clayton, 2023) and their greater likelihood of adopting climate-friendly behaviors in everyday life (Elert and Lundin, 2022) could partly explain their lower carbon footprints, particularly in food and transport consumption. However, as Bush and Clayton (2023) argue, causality may also flow in the opposite direction: women might show greater climate concern because their consumption patterns are less carbon-intensive for reasons unrelated to environmental preferences.

While our cross-sectional data do not allow us to determine the direction of causality, the evidence suggests the gap is not solely driven by differences in climate concerns. The disparity in footprints between single and non-single women, as well as between those with and without children, suggests that part of the observed gender gap in carbon footprints could be driven by gendered social roles. Furthermore, the differences observed in the consumption of high-emission goods tied to traditional masculinity, such as red meat and cars, but not for gender-neutral polluting goods like plane trips, suggest that gendered preferences pre-dating climate concerns may contribute to the gap.

Within households, the dynamics of decision-making may also play a role in shaping carbon footprints. For instance, we observe higher red meat consumption among women in couples compared to single women, and cars owned by single women are 0.13SD less carbon-intensive than those owned by single men. Given evidence that infrequently adjusted consumption goods, such as cars, account for a large share of household carbon footprints (Kuhn and Schlattmann, 2024), involving women more actively in these key decisions may help reduce overall carbon footprints. Looking across different household arrangements, our findings suggest that more balanced bargaining power may not have uniform effects across all consumption categories. In the case of food, single women emit less than women in couples, indicating that greater equality in decision-making could encourage convergence towards lower-carbon choices. By contrast, single women's transport carbon footprints exceed those of women in multi-adult households, hinting at a specialisation dynamic, where the partner with higher income may choose more carbon-intensive travel options. While policies that directly enhance women's bargaining power are limited, these findings highlight the need for further research into how intra-household decision-making dynamics influence carbon footprints.

Finally, our results suggest that information policies challenging traditional gender norms, particularly those tied to 'dominance masculinity' (De Haas et al., 2024), could indirectly reduce household carbon footprints. Campaigns that deconstruct the association of red meat consumption and car ownership with masculinity may lower male demand for these carbon-intensive goods. Similarly, addressing stereotypes that portray green consumption and vegetarianism as feminine (Brough et al., 2016; MacInnis and Hodson, 2015; Rosenfeld, 2020) could increase men's willingness to adopt pro-environmental behaviors. Conversely, recent cultural trends promoting raw meat consumption or 'all-meat diets,' often accompanied by rhetoric against plant-based diets, may inadvertently increase carbon footprints by reinforcing traditional masculine norms.[27] While these trends are rooted in conservative gender ideologies rather than climate concerns, they underscore the importance of addressing gendered perceptions in climate-related behavior.

[27] As described for instance in https://www.bps.org.uk/psychologist/meatheads-and-soy-boys.

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Appendix

A Methods to Estimate Carbon Footprints

Food Carbon Footprints

The computation of food carbon footprints relies on the matching of food consumption data from the INCA3 dataset and environmental information from the Agribalyse dataset. The INCA3 and Agribalyse datasets contain, respectively, 2,886 and 2,481 unique labels that refer to as many standardized products. Given that these datasets have not been matched at the product level before, we rely on a mixed method drawing from string matching, hand matching and natural language processing (NLP) for the matching. Doing so, we aim to find for every INCA3 product the closest product in the Agribalyse dataset to associate as precisely as possible food consumption with food environmental impacts. We proceed as follows:

- First, we select perfect string matches defined by a cosine similarity of 1.0. (e.g. the product label is 'Carot' in both datasets). This is the case for 117 INCA3 products.
- Second, we minimize errors on the most consumed products (ie largest volumes per product in the INCA3 dataset), which represent together 80% of the purchased volumes, and we minimize error on the measurement of CO_2 intensities for the top 100 emitting products (animal products). These conditions are satisfied for 363 products. For these products, we hand-check the matching and apply hand corrections for one-third (118) of the products.
- Third, we apply systematic matching based on a mixed method of NLP and key terms matching. For each method, we compute similarity scores (cosine), and we choose the best match. In most cases (94% of the products), we retain the key-terms approach against the NLP approach. The low performance of the NLP algorithm can be explained by the BERT algorithm not being specifically trained for the food vocabulary.
  - *NLP approach*: we perform NLP matching at two stages. First, we use NLP to find correspondence across subgroups between INCA3 and AGB. Then within each matched subgroup, we perform a second NLP matching at the product level. The matching is performed using CamemBERT, a deep-learning model trained for the French language.
  - *Key-terms approach*: we define a set of key terms that reflect the most commonly consumed food products in France.[28] This reduces the error, given the type of ingredient is the key driver of its carbon footprint. This way, we ensure that the type of ingredient is consistent across datasets.

[28] We retain a list of 276 key terms which reflect the most common products in the following categories: cheese, dairy, vegetable, fruit, meat, fish, snacks, starches, legumes, drinks, seasonings and culinary aids.

- Finally, we perform additional hand-checks for 14% (343) of the products matched in the previous step.

A.1 Transport Carbon Footprints

To reflect real-world lifecycle emissions per person, the following adjustments are made by the data producer to obtain trip-level emissions from transport-specific and car model-specific emission intensities:

- upstream emissions related to the energy production used in the manufacturing and transport of the vehicle are added for all modes
- for plane, non-CO_2 warming effects are added
- for cars, emissions associated with cold starts are added. These cold start emissions reflect the fact that the first minutes of a car trip emit more due to the higher fuel consumption of engines until they reach their optimal temperature while driving
- for cars and two-wheelers, the occupancy rate of the trip as declared in the survey is taken into account, and total trip emissions are divided by the number of people in the car/two-wheeler. Dividing car emissions by the number of passengers means that we do not reallocate the emissions from children's mobility to the adults in the households: a 10km car trip driving two children to a leisure activity will count as 1/3 the emissions of a 10km car trip alone. Given that women are more likely to be the ones accompanying children to their leisure activities (**?**), this choice could contribute to decreasing women's emissions.
- the upstream emissions associated with the manufacturing of the vehicle and transport infrastructure are not included in the calculations.

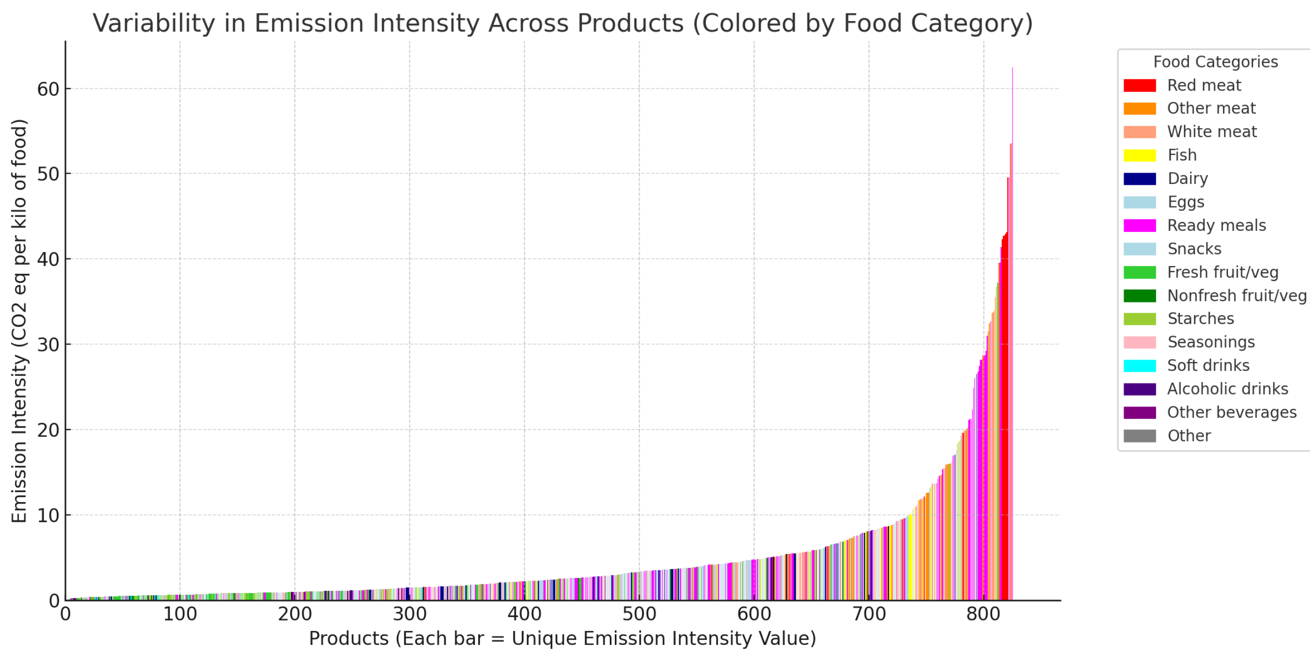
The methodology is described in greater detail in Lezec et al. (2023). We amend these emissions in two ways: first, absent information on distance per mode in multi-modal trips, the calculations assume that the entire trip is done with the main transport mode declared in the survey. We improve the measure by accounting for the distance walked in the trip.[29] Second, we add an emission factor for upstream emissions from vehicle manufacturing using data from the French Agency for the Environment (Base carbone ADEME 2023) so that emissions reflect carbon footprints and are comparable in scope to the food emissions. The only upstream emissions not included are those associated with building the transport infrastructure (roads, rail tracks), due to lack of data.

[29]We use trip-level information on the time spent walking and assume a walking speed of 4 kilometers per hour to calculate the distance walked. We proxy the distance traveled with the main transport mode with the difference between total trip distance and walking distance. We re-calculate trip-level emissions by multiplying this distance by the trip-level emission intensity implied by the trip-level emission measure provided in the survey.

B Additional Figures and Tables

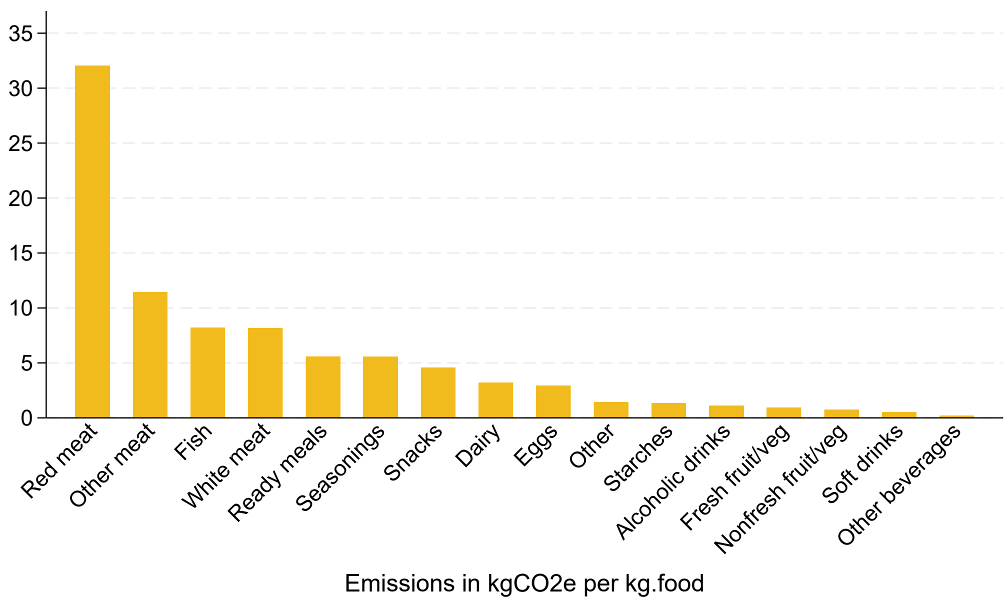
B.1 Emission Intensities

Figure B.1: Food Emission Intensity by Product Type.



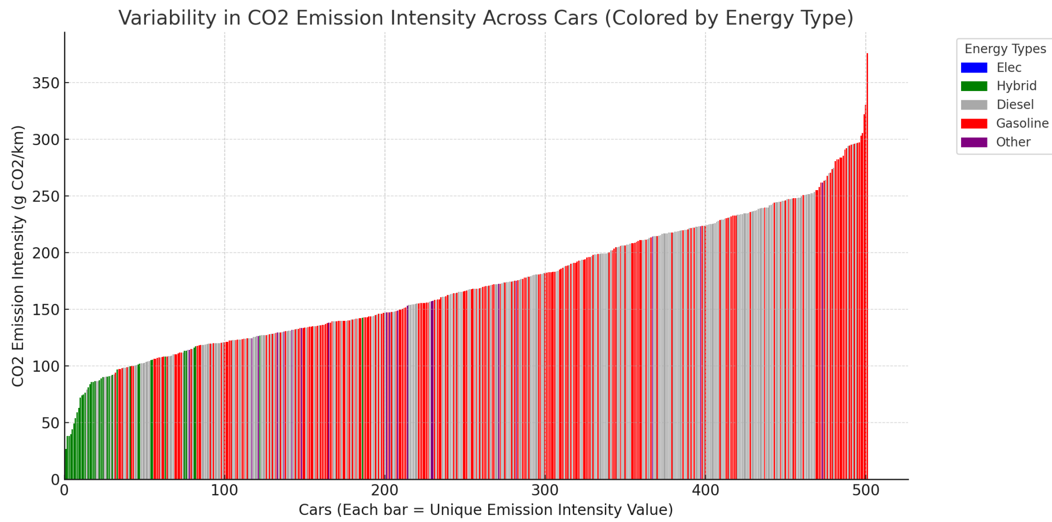
Notes: Distribution of greenhouse gas (GHG) emission intensities (in CO_2e per kilogram of food) across all food products. Each bar represents a *unique value* in the total distribution of emission intensities, sorted from lowest to highest. The visualization highlights the granularity and variability in climate impacts among different food items. Food categories are defined as follows: *Starchy food*: pasta, bread, semolina, cook-type cereals, potatoes; *Fresh fruits and vegetables*: fresh fruits, fresh vegetables; *Red meat*: beef, mutton, lamb; *White meat*: chicken, turkey, veal, rabbit, pork, poultry; *Other meat*: cold cuts, mix of meats, ham, game meat, frogs, kangaroo; *Fish*: fish and seafood; *Eggs*: hen and quail eggs; *Dairy*: cheese, milk, yoghurts; *Snacks*: sugary biscuits, jam, honey, spreads, cereal/granola bars, chocolate, pastries, breakfast drink preparation, breakfast cereals, ice cream, desserts, dry fruits and seeds, salty biscuits, olives, crisps; *Ready meals*: prepared dishes, frozen dishes, canned dishes; *Soft drinks*: sodas, syrups, juices; *Alcoholic drinks*: cocktails, liquors, wine; *Other beverages*: coffee, tea, infusions, water, chicory; *Seasonings*: spices, oil, vinegar, butter, croutons, breadcrumbs, raw pastry, confectionery flavours, flour, prepared crust, coconut milk, cream, lemon juice, herbs, dry herbs, garlic, onion; *Non-fresh fruits and vegetables*: canned fruits and vegetables, frozen fruits and vegetables, lyophilised vegetables, beans, dried vegetables, packaged vegetables; *Other*: baby food, chewing gum, food supplements. Source: INCA3 food intake-by-day data (N=256,301). Weighted averages across food intakes of the same food category and day, using food quantities as weights. Source: Agribalyse (2017).

Figure B.2: Emission Intensity by Food Category Aggregated in 15 categories.



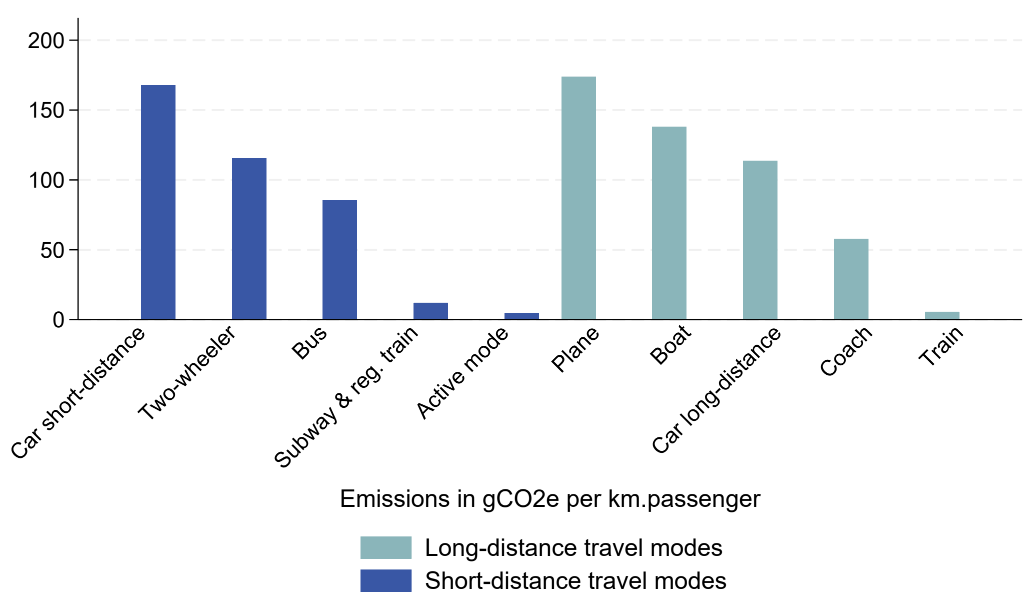
Notes: Volume weighted CO_2e emissions in kilograms expressed in kilogram of the food consumed. Weighted averages across food intakes of the same food category and day, using food quantities as weights. Food categories are defined as follows: *Starchy food*: pasta, bread, semolina, cook-type cereals, potatoes; *Fresh fruits and vegetables*: fresh fruits, fresh vegetables; *Red meat*: beef, mutton, lamb; *White meat*: chicken, turkey, veal, rabbit, pork, poultry; *Other meat*: cold cuts, mix of meats, ham, game meat, frogs, kangaroo; *Fish*: fish and seafood; *Eggs*: hen and quail eggs; *Dairy*: cheese, milk, yoghurts; *Snacks*: sugary biscuits, jam, honey, spreads, cereal/granola bars, chocolate, pastries, breakfast drink preparation, breakfast cereals, ice cream, desserts, dry fruits and seeds, salty biscuits, olives, crisps; *Ready meals*: prepared dishes, frozen dishes, canned dishes; *Soft drinks*: sodas, syrups, juices; *Alcoholic drinks*: cocktails, liquors, wine; *Other beverages*: coffee, tea, infusions, water, chicory; *Seasonings*: spices, oil, vinegar, butter, croutons, breadcrumbs, raw pastry, confectionery flavours, flour, prepared crust, coconut milk, cream, lemon juice, herbs, dry herbs, garlic, onion; *Non-fresh fruits and vegetables*: canned fruits and vegetables, frozen fruits and vegetables, lyophilised vegetables, beans, dried vegetables, packaged vegetables; *Other*: baby food, chewing gum, food supplements. Source: INCA3 food intake-by-day data (N=256,301).

Figure B.3: Cars Emission Intensity by Fuel Type.



Notes: Distribution of CO_2e emission intensities (in g CO_2e/km) for cars. Each bar corresponds to a *unique value* in the total distribution of cars emissions, sorted from lowest to highest, rather than to an individual vehicle. Bars are colored according to the vehicle's energy type associated with each intensity value. *Other* represents liquefied petroleum gas cars. Source: EMP data.

Figure B.4: Emission Intensity by Transport Mode Category.



Notes: CO_2e emission intensities (in g CO_2e/km) for different transportation modes. Source: EMP trip-level data (N=44,759 for short-distance trips and N=30,938 for long-distance trips). Weighted averages across trips using the same transport mode category, using distances as weights.

B.2 Summary Statistics

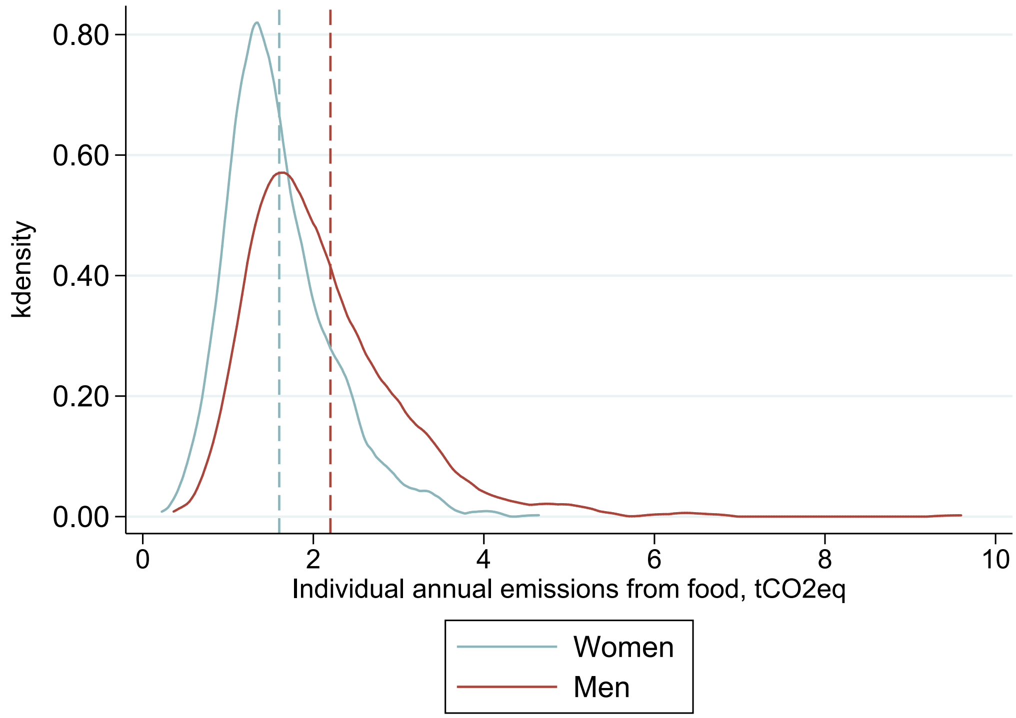
Table B.1: Summary Statistics: Sociodemographics by Sample

	Food		Transport	
	Mean	SD	Mean	SD
Household size	2.30	1.20	2.20	1.20
Gender = Female	0.58	0.49	0.54	0.50
Age				
18-44	37.00	-	33.00	-
45-64	39.00	-	40.00	-
65-79	24.00	-	27.00	-
Work Status				
Pupil/Student	3.68	-	3.71	-
Employed	53.84	-	50.38	-
Other inactive	6.84	-	6.51	-
Pensioner	5.04	-	5.59	-
Other status	30.60	-	32.98	-
Education				
Less than secondary or vocational degree	39.00	-	50.00	-
End of high school diploma	19.00	-	19.00	-
Higher education degree below 2 years	21.00	-	13.00	-
Higher education degree above 2 years	20.00	-	18.00	-
Observations	2,121		11,325	

Notes: Summary statistics by sample for the main comparable sociodemographic variables. Income is not included because the definition differs widely across samples. In the Transport survey income is defined by decile, while it is interval-coded in the Food survey.

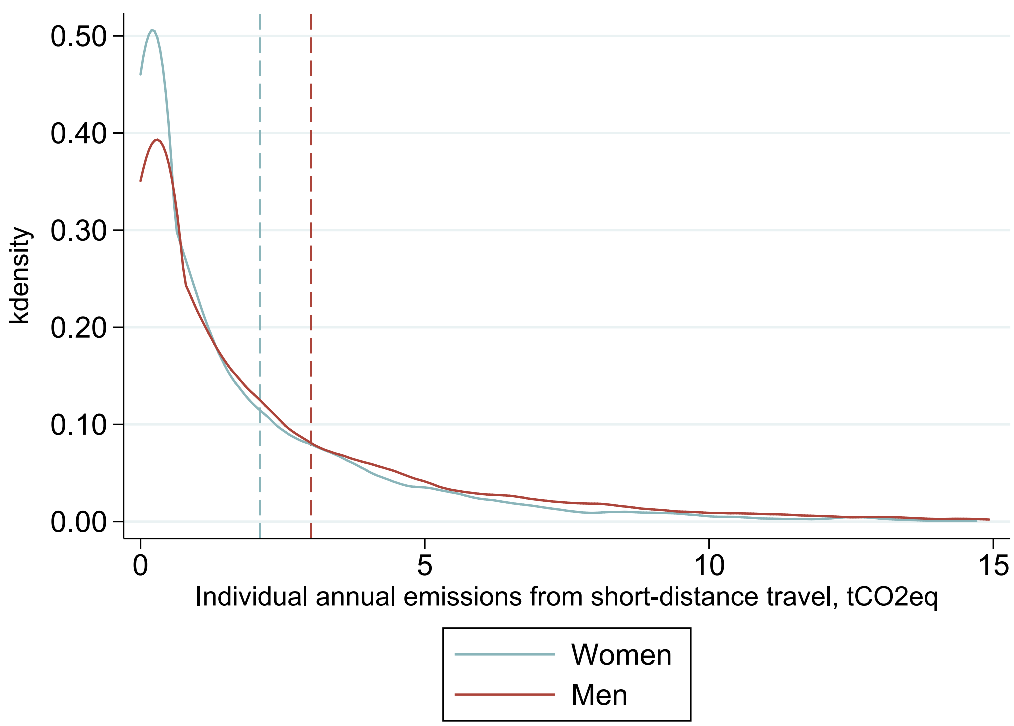
B.3 Distribution of Carbon Footprints by Gender

Figure B.5: Distribution of Yearly Food Carbon Footprints.



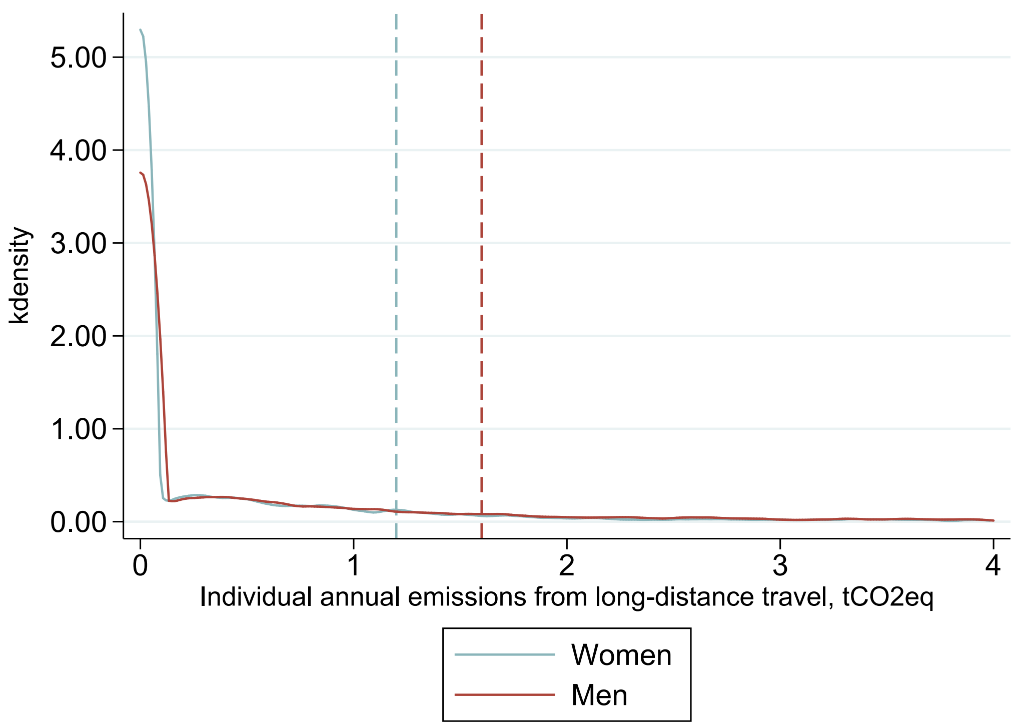
Notes: The blue dashed line indicates the average annual carbon footprints for women and the red dashed line the average annual carbon footprints for men, calculated with survey weights. Source: INCA3 (N=2,121).

Figure B.6: Distribution of Yearly Short-Distance Travel Carbon Footprints.



Notes: The blue dashed line indicates the average annual carbon footprints for women, and the red dashed line indicates the average annual carbon footprints for men, calculated with survey weights. Source: EMP (N=12,077).

Figure B.7: Distribution of Yearly Long-Distance Travel Carbon Footprints.



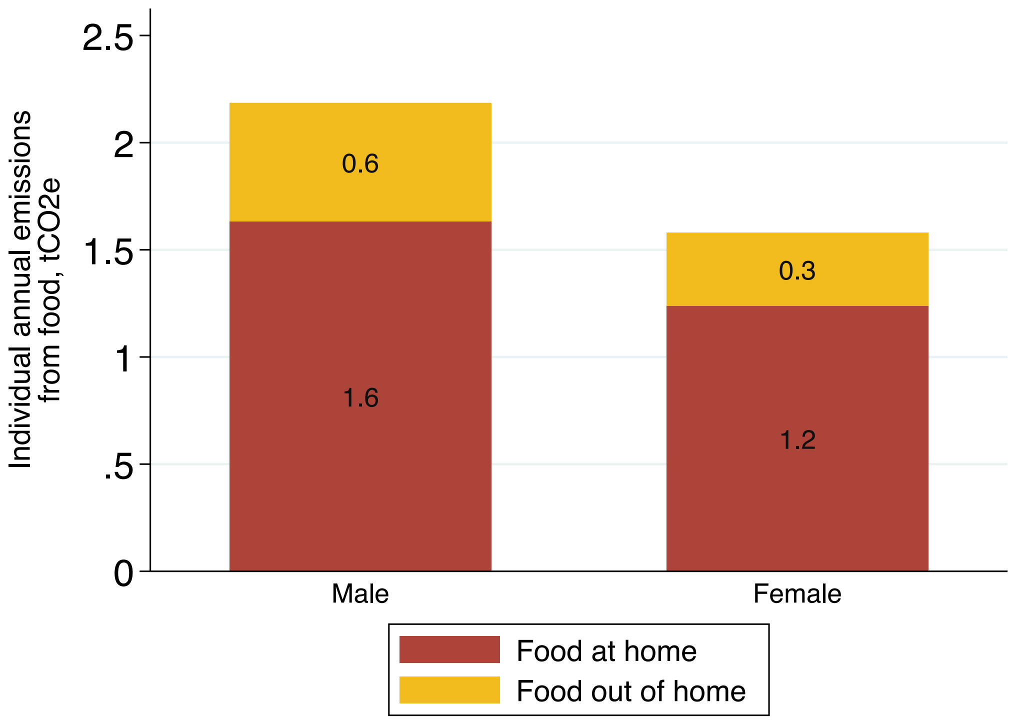
Notes: The blue dashed line indicates the average annual carbon footprints for women and the red dashed line the average annual carbon footprints for men, calculated with survey weights. Source: EMP (N=12,077).

B.4 Decomposition in Consumption Categories

Figure B.8: Decomposition of Transport Carbon Footprints Between Work and Non-Work.

Notes: Work emissions are emissions from trips having a work-related purpose, either commuting or a business trip. Non-work emissions are emissions from trip having as purpose either leisure, shopping or escorting or another purpose. Source: transport: EMP (N=12,077). Averages calculated with survey weights.

Figure B.9: Decomposition of Food Carbon Footprints Between Food at Home and Out of Home.



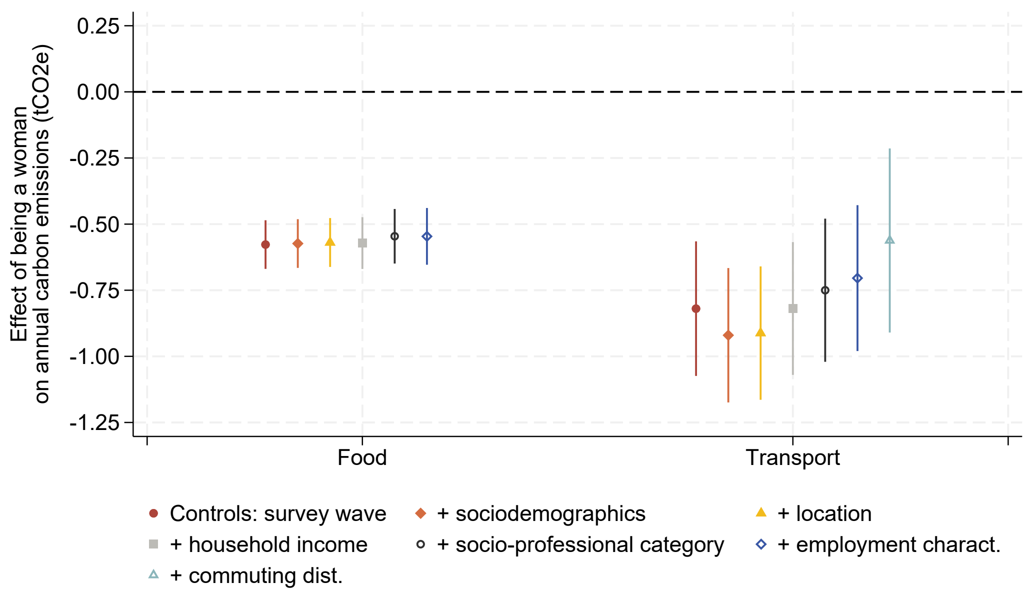
Notes: Food out-of-home includes food taken at friends' or relatives' home, on the workplace or at restaurants and take-aways. Source: INCA3 (N=2,121). Averages calculated with survey weights.

B.5 Subsample of Employed Individuals

Figure B.10: Individual CO_2 Carbon Footprints Associated with Annual Food Consumption and Transport Use by Gender, Employed Individuals.

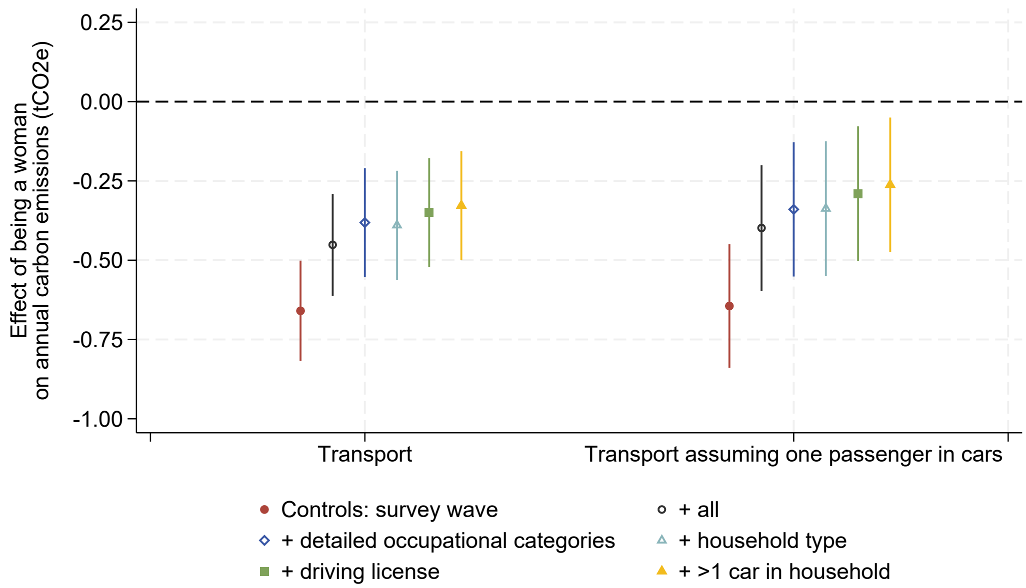
Notes: Source: Food consumption: INCA3 (N=1,142 for all employed); transport: EMP (N=5,663 for all employed). Averages calculated with survey weights.

Figure B.11: Conditional Gender Gap in Carbon Footprints, Sample of Individuals in Employment.



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "+ sociodemographics" additionally controls for age, education and household size. "+location" additionally controls for size of the urban unit of residence. "+household income" additionally controls for household income. "+socio-professional category" additionally controls for socio-professional category and employment status. "+employment charact." additionally includes an indicator variable for whether the individual works part-time and an indicator variable for whether the person has an atypical working time. "+ commuting dist" additionally controls for commuting distance. Source: Food consumption: INCA3 (N=1,142 for all employed); transport: EMP (N=5,663 for all employed).

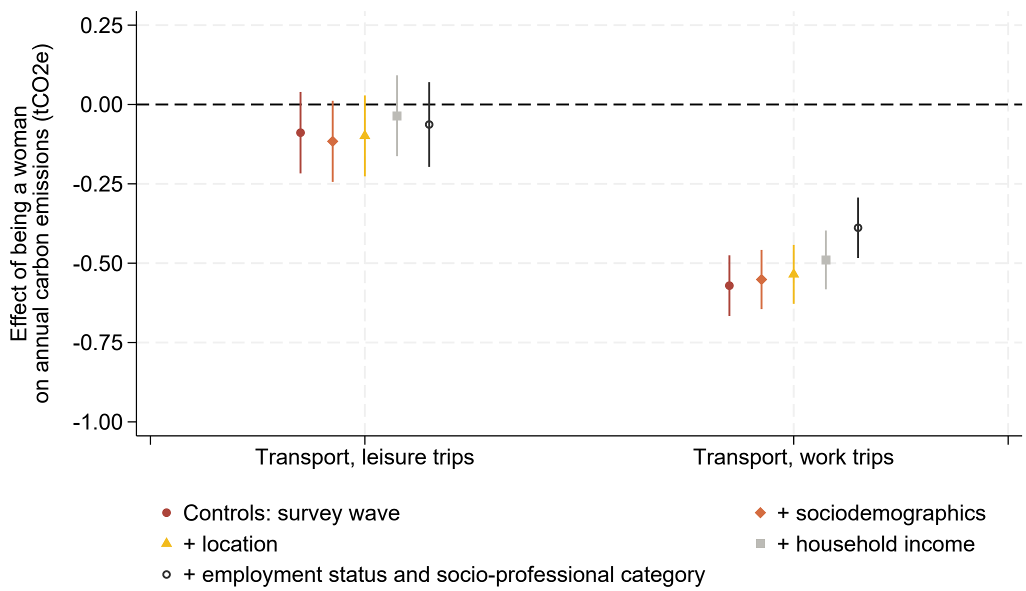
Figure B.12: Conditional Gender Gap in Transport Carbon Footprint, additional controls and robustness checks.



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "all" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status and broad socio-professional category. "+ detailed occupational categories" replaces the five occupational categories with more detailed ones. Source: transport: EMP (N=12,077)

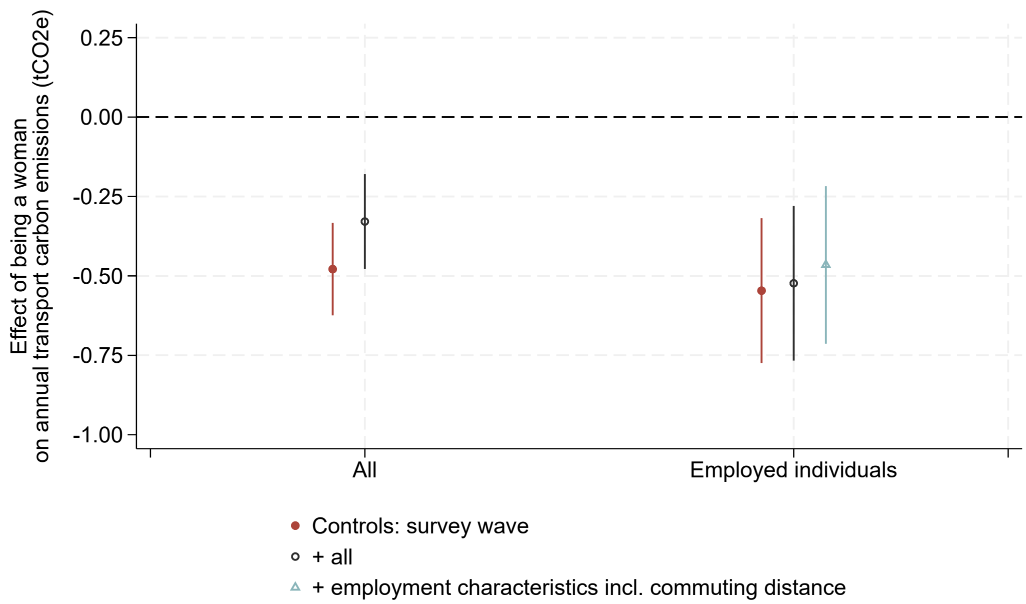
B.6 Conditional Gender Gap in Transport Carbon Footprints with Additional Controls, Full Sample.

Figure B.13: Conditional Gender Gap in Transport Carbon Footprints, work-related vs non-work emissions



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "all" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status and broad socio-professional category. "+ detailed occupational categories" replaces the five occupational categories with more detailed ones. Source: transport: EMP (N=12,077)

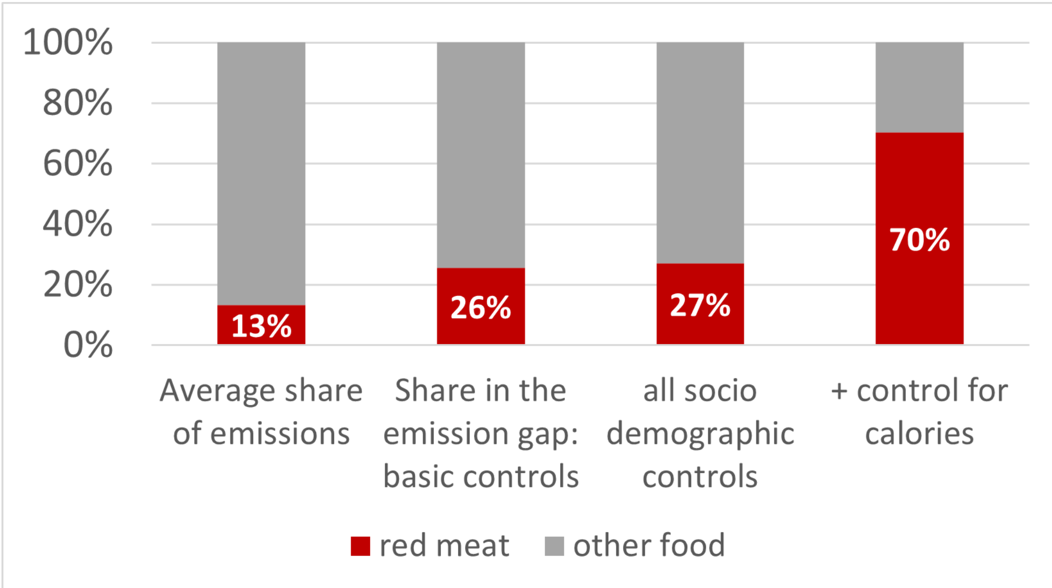
Figure B.14: Conditional Gender Gap in Transport Carbon Footprints, Excluding Work-related Emissions outside Commuting.



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each consumption category, including an increasing number of control variables. "Controls: survey wave" only controls for the time of year when the survey is conducted. "+ all" additionally controls for age, education and household size, size of the urban unit of residence, household income, employment status and socio-professional category. "+employment characteristics incl.commuting distance" also controls, among the employed, for part-time work status, working night shifts, and commuting distance. Source: EMP (N=12,077)

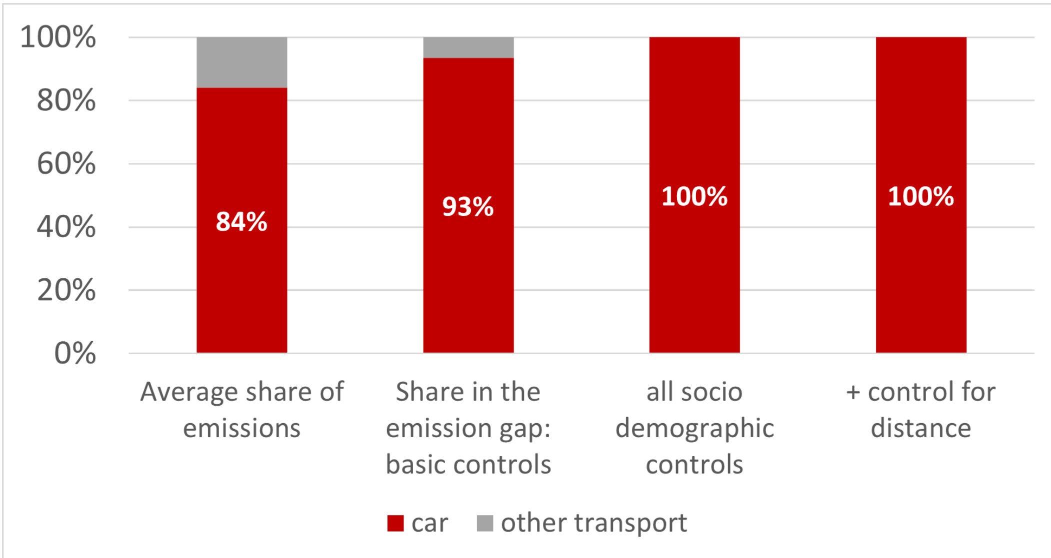
B.7 The role of red meat and car emissions in the gender gap in carbon footprints.

Figure B.15: Contribution of red meat to the food gender gap



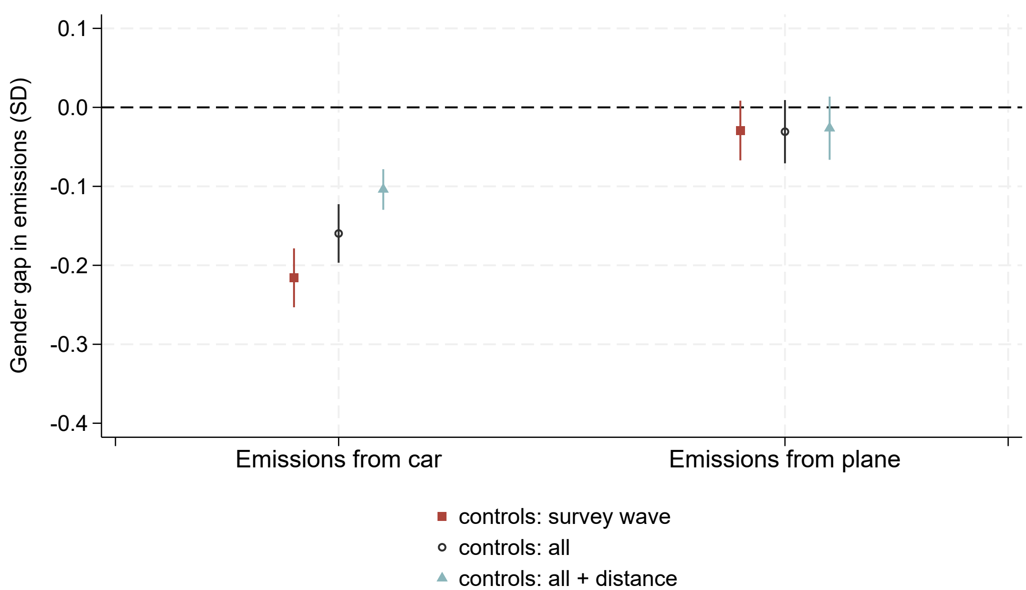
Notes: The first bar shows the relative share of red meat (red) compared to other food (gray) in total carbon equivalent emissions for the average individual. The second to fourth bars shows the share of the conditional gender gap in food carbon footprints that is explained by the gap in red meat emissions. This percentage is obtained by dividing the coefficient on the gender dummy for the regression using red meat emissions as outcome by the coefficient on the gender dummy using total food carbon footprints as outcome. Source: INCA3 (N=2,121).

Figure B.16: The contribution of car to the transport emission gap



Notes: The first bar shows the relative share of car (red) compared to other transport (gray) in total carbon equivalent emissions for the average individual. The second to fourth bars shows the share of the conditional gender gap in car emissions that is explained by the gap in red meat emissions. This percentage is obtained by dividing the coefficient on the gender dummy for the regression using car carbon footprints as outcome by the coefficient on the gender dummy using total transport carbon footprints as outcome. Source: EMP (N=12,077).

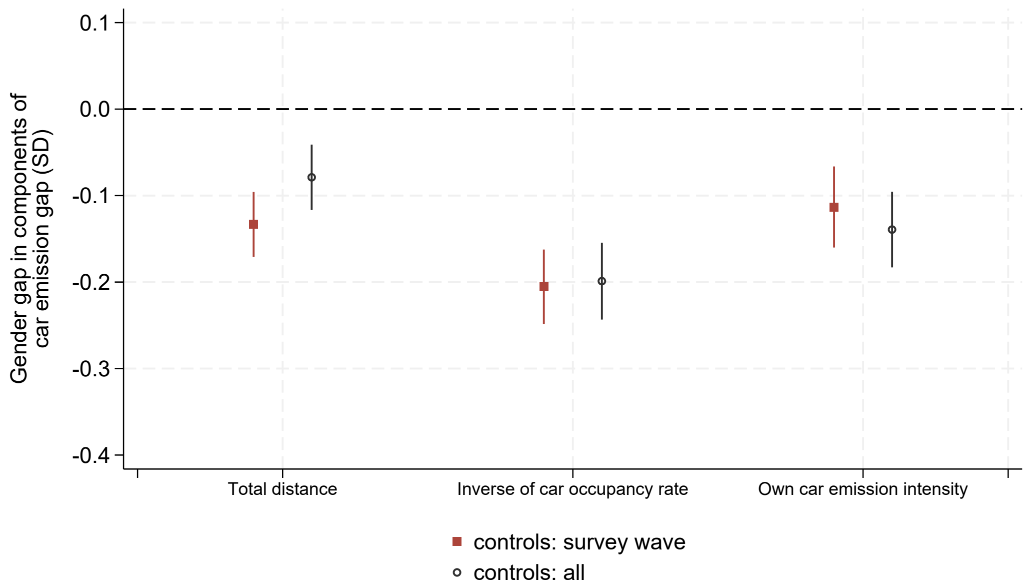
Figure B.17: Gender Gap in Car vs Plane Emissions.



Notes: of standardized emissions from car trips and plane trips. The point estimates and 95% confidence intervals in blue show the estimated coefficient for the gender dummy "female". "Controls: survey wave" only controls for the time of year when the survey is conducted "controls: all" additionally controls for age, education, household size, size of the urban unit of residence, household income and employment status and socio-professional category. "Controls: all + distance" additionally controls for reported total distances traveled. Source: EMP (N=12,077).

B.8 Components of car emission gap

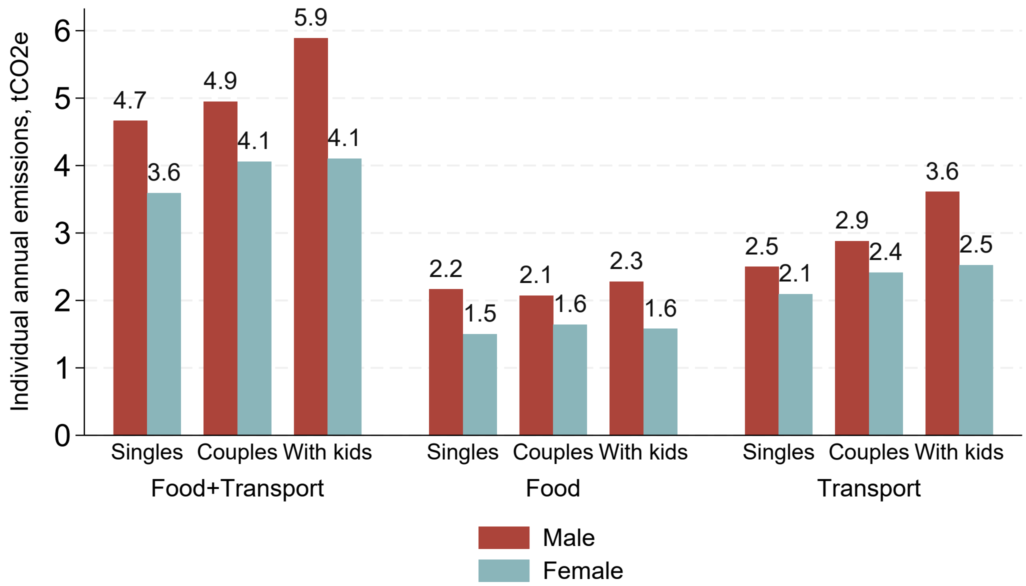
Figure B.18: Gender Gap in Components of Car Emission Gap.



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions, one for each determinant of the gender car emissions gap, including an increasing number of control variables. The first measure is the standardized total distance traveled; the second is the standardized inverse of the occupancy rate for car trips, for the subsample of individuals with at least one car trip; the third one is the standardized emission factor of the car owned by the individual, for the subsample of single individuals. Source: EMP (N=11,047 for distance, N=8,017 for car occupancy rate, and N=7,036 for singles' car emission intensity).

B.9 Unconditional Gender Gap in Food Carbon Footprints by household arrangement.

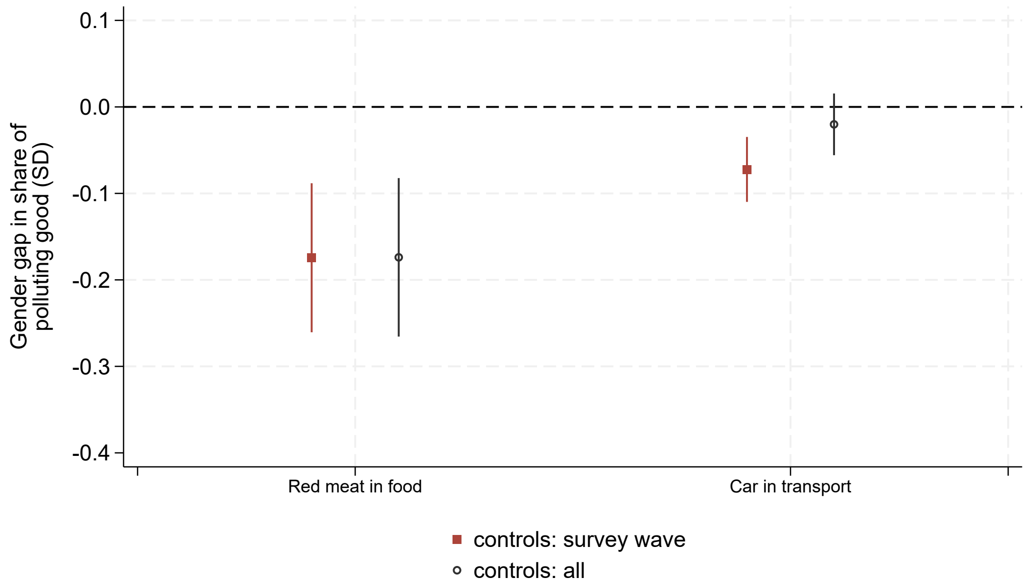
Figure B.19: Individual CO_2 Emissions Associated with Annual Food Consumption and Transport Use by Gender and Household Composition.



Notes: Source: Food consumption: INCA3 (singles without children: N=584; couples without children: N=800; couples with children: N=654); transport: EMP (singles without childrens: N=3,629; couples without children: N=3,820; couples with children: N=3,917).

B.10 Gender gap in the share of polluting good

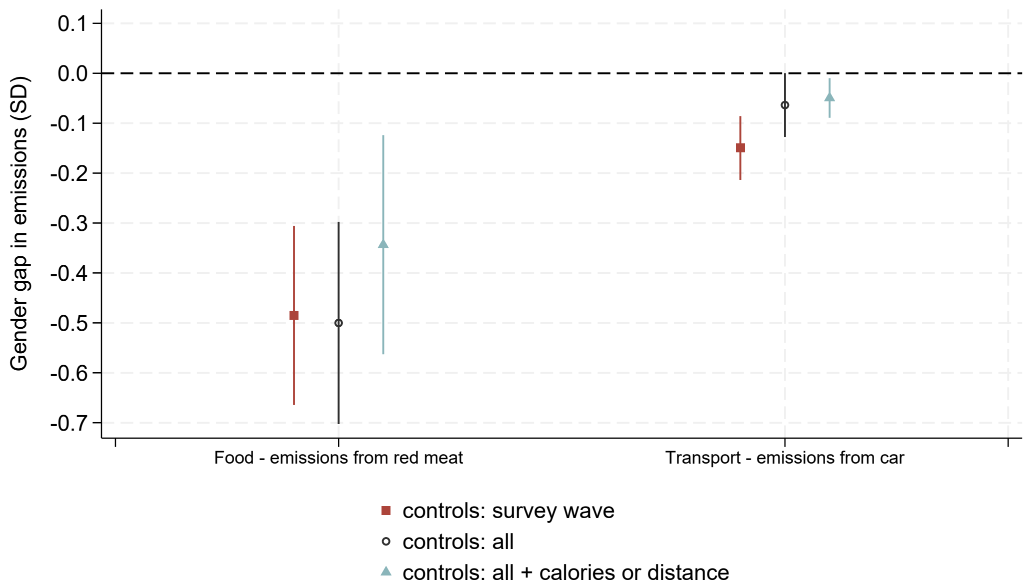
Figure B.20: Food: Gender Gap in the share of red meat in food volumes and the share of car in total distances



Notes: The point estimates and 95% confidence intervals show the estimated coefficient for the gender dummy "female" from separate OLS regressions of standardized share of red meat volume in total food volume, and share of kilometers by car in total kilometers traveled. "Controls: survey wave" only controls for the time of year when the survey is conducted "controls: all" additionally controls for age, education, household size, size of the urban unit of residence, household income and employment status and socio-professional category. Source: INCA3 (N=2,121); EMP (N=10,967)

B.11 Gender gap in red meat and car emissions, singles

Figure B.21: Food: Gender Gap in Red Meat and Car emissions, singles



Notes: The point estimates and 95% confidence intervals in red show the estimated coefficient for the gender dummy "female" from separate OLS regressions of standardized emissions from red meat consumption and standardized emissions from car trips. The point estimates and 95% confidence intervals in blue show the estimated coefficient for the gender dummy "female". "Controls: survey wave" only controls for the time of year when the survey is conducted "controls: all" additionally controls for age, education, household size, size of the urban unit of residence, household income and employment status and socio-professional category. "Controls: all + calories or distance" additionally controls for reported daily calories intake for the regression on food and for reported total distances traveled for the regression on transport. Source: INCA3 (N=545); EMP (N=3,490)

Table B.2: Oaxaca-Blinder Decomposition for Food and Transport

	Food		Transport	
Overall Mean (in tCO_2e)				
Men	2.120 (0.0326)		3.062 (0.0635)	
Women	1.591 (0.0178)		2.408 (0.0513)	
Total Difference	0.528 (0.0371)		0.654 (0.0816)	
Observations	1,957		11,016	
	(1) **No Calories**	(2) **With Calories**	(3) **No Distance**	(4) **With Distance**
Decomposition (in tCO_2e)				
Explained part	0.0443 (0.0139)	0.395 (0.0300)	0.203 (0.0353)	0.407 (0.0584)
Unexplained part	0.484 (0.0360)	0.133 (0.0335)	0.451 (0.0837)	0.247 (0.0658)
Decomposition (in %)				
Explained share	8.39	74.81	31.04	62.23
Unexplained share	91.66	25.19	68.96	37.77

Notes: Columns 1 to 4 show results obtained from two-fold Oaxaca-Blinder decompositions. Robust standard errors are in parentheses. Specifications (1) and (2) correspond to different control sets for food (without calorie intake and controlling for calorie intake), and (3) and (4) correspond to different control sets for transport (with and without traveled distance).